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Three Essays on the Role of Expectations in Business Cycles

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Ces opinions doivent être considérées comme propres à leur auteur.

For my family

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Contents

List of Tables

List of Figures

General Introduction

The concept of expectations lies at the very heart of research in economics. Individuals' decisions are guided by their objectives and limited by their constraints. They are also made in a social system rife with uncertainty. If an individual wants to make the best decision possible, she must address this uncertainty by forming expectations about what she thinks will happen in the future. We might say, then, that there is no decision-making without expectations.

Since the work of Pigou (1927) and Keynes (1936), there has been a field of research in economics dedicated to studying the role of expectations in business cycles. Economists working within this field have suggested that business cycles can emerge from changes in individuals' expectations that are not necessarily related to economic fundamentals. Despite the large number of papers which have arrived at this conclusion, the sub-prime crisis, the European sovereign debt crisis, and the adverse macroeconomic environment triggered by these events have demonstrated that expectations and their effects are not yet fully understood. Since the 1980s, more and more scholars have mounted theoretical investigations into expectations' role in business cycles, but few of these studies have been fully successful when confronted with data. Conversely, it is challenging to find data appropriate for measuring expectations beyond surveys.

This study asks: what is the role of expectations in business cycles? My primary goal in this thesis is to bring together theoretical and empirical evidence of expectation shocks in pursuit of this question. To this end, I use an eclectic battery of strategies, from theoretical analysis, calibration, and data confrontation to techniques taken from the computer sciences such as web scraping, machine learning, and textual analysis. I also take up the task of measuring expectations by using innovative data from the social media platform Twitter. By adopting a variety of approaches, I have unearthed different sorts of evidence, all of which suggests that expectations do, indeed, play a role in business cycles.

Role of Expectations in Recent Economic and Financial Crises

The field of research in economics that studies expectations has experienced a burst of activity in recent years. Figure 1 shows the number of research papers per year in the field of economics mentioning the words "expectations" and "crisis" from 1980 to 2018. The number of papers increased during this period, intensifying especially after 2007. This dramatic increase in research on this topic demonstrates a new surge in scholarly interest in expectations, likely triggered by their precise role in both the subprime crisis and the European sovereign debt crisis.

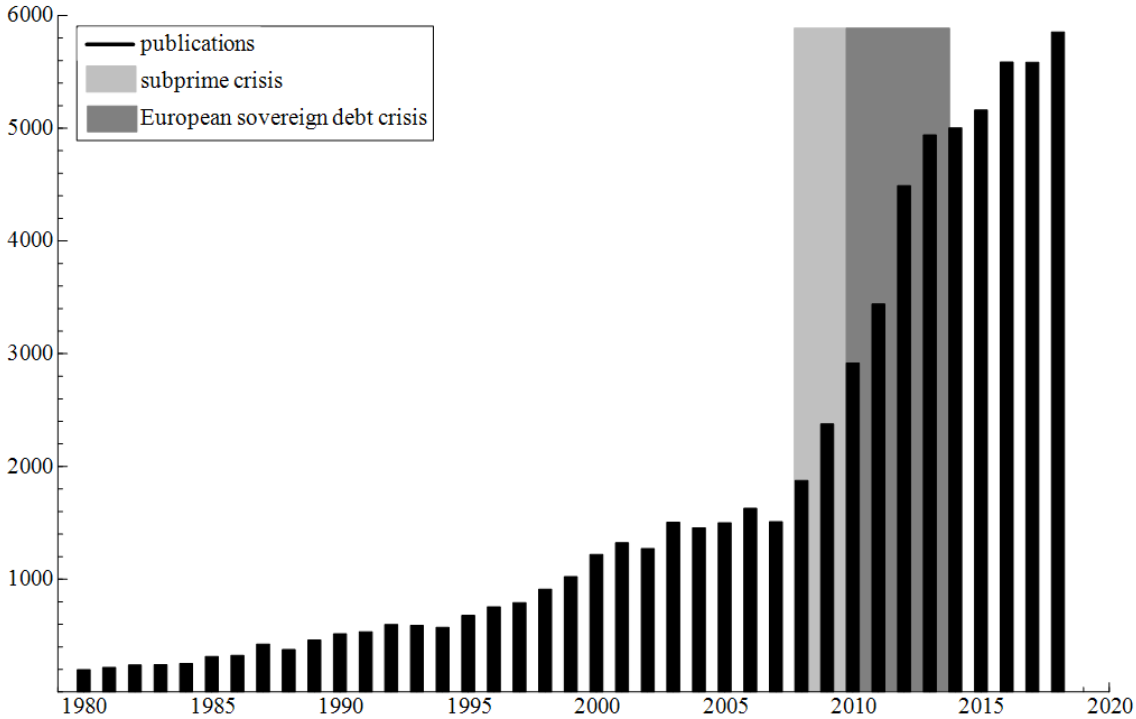

Figure 1 – Number of Research Papers Per Year in the Field of Economics Mentioning the Words "Expectations" and "Crisis" From 1980 to 2018.

The subprime crisis hit the world economy in 2007-08. Its origins lie in the burst of a housing bubble in the United States. As we know, expectations play a central role in the making and subsequent collapse of a bubble: a cycle wherein the price of an asset surges because of exuberant market behavior. In other words, bubbles appear when the market assumes that the asset's price in the future will be higher than its price today. Market participants coordinate around this assumption, which raises demand for the asset, which in turn increases the price. When market participants begin to revise their expectations and come to believe that tomorrow's price will be lower than today's, they begin to sell off that asset, and the bubble bursts.

The mortgage bubble was one of the primary mechanisms at play during the financial crisis. A major contributing factor to the severity of this bubble, and by extension the subprime crisis, was the securitization of subprime mortgages into collateralized debt obligations and mortgage-backed securities, which diluted the perceived risk associated with toxic mortgages. In the case of the subprime crisis, securitization allowed investors to see these mortgages as low-risk assets, which increased the demand for them, further feeding the bubble.

Because of the interconnections between financial markets, the burst of the US housing bubble became a global problem. Its effects, along with the Greek crisis, contributed to the European sovereign debt crisis. That is: because governments both dedicated significant resources to mitigating the effects of the subprime crisis on the financial markets (by buying toxic assets, for example) and experienced a natural increase in deficit due to automatic stabilizers, they became at risk of default. The sovereign bond yields of the European periphery countries were, it seems, unreasonably high, which suggests that factors in addition to economic fundamentals were at play in the pricing of sovereign debt (See De Grauwe and Ji 2013). Some economists have given expectations a primary role here: it seems as though investors were pessimistic enough about these countries' solvency that the debt was priced higher than it would have been if only economic fundamentals were at work. In the periphery countries, very high interest rates then put them at risk of self-fulfilling default crises.

Expectations are central to a self-fulfilling default crisis. Specifically, default occurs through changes in expectations about how market participants assess the default risk of a country. When investors become pessimistic about a country's solvency, they require higher and higher interet rates on government bonds due to what they perceive as an increased risk, which increases the speed at which debt is accumulated. More debt accumulation increases the probability that the country becomes insolvent, feeding investors' fears of default, and so on, until the country actually defaults. Default is thus triggered primarily by a self-fulfilling prophecy. In the case of the European sovereign debt crisis, the periphery countries avoided default in part because the president of the European Central Bank, Mario Draghi, managed investors' expectations by credibly committing to acting as lender of last resort. (I go into more detail about Draghi's statements on the OMT program in my second chapter.)

These two crises manifest expectations and their effects in different ways. In the subprime crisis, expectations-driven shocks in the financial sector (among other factors, including the securitization I mention above) profoundly impacted the real economy. In the European sovereign debt crisis, investors' negative expectations contributed to the pricing of countries' sovereign debt and, ultimately, their risk of default—and, in the end, it was a change of expectations (along with other factors) that stopped the periphery countries from actually defaulting. As these events have proven, expectations can pose a danger to economies when mismanaged, and can also be a tool to defuse crises when well understood. More research is needed to better understand and subsequently manage expectation shocks' diverse manifestations in different areas of the economy.

Overview of the Literature on the Role of Expectations in Business Cycles

The literature on expectations in business cycles often draws on this concept of "animal spirits" that Keynes (1936) proposes in the following quotation:

> "Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations, whether moral or hedonistic or economic. Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of animal spirits—a spontaneous

> urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities."

Keynes here suggests that some part of agents' decisions depends on market psychology in addition to (or perhaps rather than) economic fundamentals. Economists have proposed different interpretations of Keynes' original concept of "animal spirits", and the approaches that I here broadly focus on agree that decisions made according to market psychology are compatible with the rational expectations assumption. This concept of "animal spirits" has generated two strands of literature. On the one hand, there are economists who argue that business cycles occur because of changes in expectations that are not necessarily derived from changes in economic fundamentals. On the other hand, some economists believe business cycles to be the result of information signals that relate to future developments in economic fundamentals.

Economists working in the first strand of the literature on expectations in business cycles study the ways in which agents' expectations can create self-fulfilling prophecies (also known as sunspot equilibria). This area of study arose during the 1970s and 1980s with a seminal paper (Cass and Shell 1983) that elaborates on the concept of sunspot equilibria developed by nineteenth-century economist William Jevons: the notion that if agents believe an event will increase the price of an asset (for example), demand for that asset will increase, thus validating their initial belief. This literature is very rich, and in discussing it I mention only key papers that are directly relevant to this thesis.

Tracing one thread of the literature on sunspots brings us to Benhabib and Farmer (1994), who created the first sunspot model using the framework of the real business cycle (RBC) literature in order to explain fluctuations. In my first chapter, I draw on the work of Benhabib and Wen (2004), who show that when correlated with fundamental shocks, one-sector sunspot models can explain many aspects of observed business cycles. A second thread of the sunspot literature aims to incorporate sunspots into sovereign debt crisis frameworks to investigate whether these crises could be self-fulfilling. Calvo (1988) was the first to apply the concept of the bank run developed by Diamond and Dybvig (1983) to a sovereign debt crisis framework. Using the theoretical concept of self-fulfilling default, a number of recent papers have explained the mechanisms behind the European sovereign debt crisis, including Lorenzoni and Werning (2013), Tirole (2015), Corsetti and Dedola (2016) and Roch and Uhlig (2018). My second chapter draws on these papers, especially Corsetti and Dedola (2016) and Roch and Uhlig (2018), and contributes to this literature by finding empirical evidence in support of the mechanisms they describe. My third chapter investigates the link between political climate and the pricing of sovereign debt.

A new approach to sunspots was developed during the 2010s. These scholars, working within this "sentiment" literature, redefine the concept of sunspots using models based on imperfect information that generates multiple correlated equilibria. See among others Angeletos and La'O (2013), Benhabib, Wang, and Wen (2015), Benhabib, Liu, and Wang (2016, 2019)

Economists working in the second strand of literature inspired by Keynes' animal spirits redefine the concept as a signal extraction problem concerning information about future changes in economic fundamentals. This literature is known as the "news and noise" literature, first developed by Beaudry and Portier (2004, 2006). Agents receive "news" when the signal is perfect and the change in economic fundamentals does indeed occur ex-post. When the information that the signal transmits is imperfect, agents receive what is called "noise", and must change their behavior in order to counteract their previous actions. Jaimovich and Rebelo (2009) first proposed a theoretical model that could explain salient features of business cycles based on the concept of news shocks. Blanchard, L'Huillier, and Lorenzoni (2013) empirically investigated the role of news and noise in the US economy, providing evidence that noise shocks can explain a significant share of consumption fluctuations.

Chapter summaries

The following includes brief summaries of the context and main results of each chapter.

Chapter One

This chapter is based on a joint work with Frédéric Dufourt and Alain Venditti (both of Aix-

Marseille School of Economics). This chapter argues that business cycles can result from self-fulfilling prophecies. We begin by considering that if one wants sunspot models to be more convincing, they should replicate the main stylized facts of a traditional demand shock: a procyclical comovement of the main aggregate variables, and a hump shaped response of output. The benchmark model, Benhabib and Wen (2004) (BW), replicates the procyclical comovement, but it does not replicate the hump shaped dynamics of output. The following question then naturally follows: can we overcome the inability of the BW model in accounting for the stylized facts in response to a sunspot shock?

In this chapter, our presumption is that the initial model considered by BW may be too constrained regarding the choice of preferences and production function. On the one hand, Benhabib and Wen use a utility function that is logarithmic in consumption and linear in labor, which implies that the intertemporal elasticity of substitution in consumption is fixed and equal to one. On the other hand, the production function is of the Cobb-Douglas type, which implies a unit elasticity of capital labor substitution.

We thus consider an enlarged version of the BW model (a one-sector stochastic growth model with variable capacity utilization and positive externalities) by considering more general specifications for preferences and the production function. The four key parameters of this model are the degree of increasing returns to scale, the elasticity of intertemporal substitution in consumption, the elasticity of capital labor substitution, and the aggregate labor supply elasticity. In the chapter, we derive all the theoretical conditions that generate indeterminacy, a necessary condition for generating sunspot shocks. We then calibrate the model and show that the model tends to perform better, as far as the replication of empirical facts is concerned, when the values of the key parameters are set in the upper range of their empirical estimates.

For our primary result, we replicate the hump-shaped dynamic of output (together with the procyclical comovement of the main aggregate variables). We have this result because under such a calibration, the model is very close to the hopf bifurcation and the subsequent invariant orbit, therefore influencing the output's hump-shaped response. However, this dynamic is too persistent and not amplified enough for the model to be fully confronted to the data, making our contribution a theoretical one.

This chapter contributes to the literature in several ways. First, we provide a model that can better replicate the stylized facts of a demand shock than the benchmark model. By improving the theoretical puzzle, this chapter brings us one step closer to a fully convincing explanation of business cycles based on sunspots/self-fulfilling prophecies. Second, we perform a detailed theoretical analysis of local stabilities and local bifurcations as a function of various structural parameters, as well as a detailed quantitative assessment that complements the results of the BW model, describing completely the dynamic properties of the model.

Chapter Two

The second chapter of my thesis is a joint work with another PhD Candidate, Michael Stiefel (University of Zürich). The context of the chapter is as follows: in summer 2012, the eurozone was on the verge of breaking up. The European Central Bank took the markets by surprise by signalling that it was ready to play its role of lender of last resort by gradually announcing the OMT program: an unlimited bond-buying program on the secondary market. Interestingly, even though the program was never actually activated, we observe a structural break in the sovereign spreads of the crisis countries.

We take one of our cues from the theoretical sovereign debt literature, which predicts that the self-fulfilling default equilibrium can be ruled out if markets believe that the central bank will act as the lender of last resort (Corsetti and Dedola 2016 and Roch and Uhlig 2018). In combination with this theoretical prediction, the events of summer 2012 prompt us to ask the following research question: can changes in belief about the central bank intervention explain the changes in sovereign bond spreads?

Our challenge is to measure the belief about how likely the European Central Bank is to intervene. We hypothesize that one could proxy this belief from Twitter data. We collect tweets using web scraping techniques, collecting 50,000 English tweets from July 30th to October 1st 2012. Each of the tweets includes one of the following key word combinations: “ECB Draghi”, “ECB bailout” or “bailout Draghi”. From this information, we create a belief index. A tweet is labelled "1" if the tweet suggests the bailout is considered to be likely, "-1" if the bailout is not considered to be likely, and "0" if it is neutral. To assign these labels, we manually label a random sample of 20 percent of the tweets. We then use textual analysis and machine learning to predict the remaining 80 percent, using the 20 percent sample as a training sample.

The main result of this chapter is the following: a one-standard deviation increase in the lagged changes in the belief index is associated with a 6 basis point reduction in the 10-year sovereign bond spreads of the crisis countries relative to the non-crisis countries. This result follows a pooled panel estimation of 9 EMU countries, is significant at a 1 percent confidence level, and holds when controlling for financial uncertainty, macoreconomic surprises and event dummies for the three key events that we examine. We show that these changes in beliefs affected the 2-year and 5-year sovereign spreads, as well.

Our results demonstrate that it is possible to learn from social media data how news announcements are received by the public, and how they impact belief formation. Our methods improve upon typical event studies by capturing anticipation and delayed reactions that are outside the event window and by distinguishing between the importance of different announcements. Our results also suggest that a credible commitment to unconventional monetary policy can be used as a coordination device during a sovereign debt crisis.

Chapter Three

This chapter is a joint work with another PhD candidate, Laura Sénécal (Aix-Marseille School of Economics). This chapter engages a broader concept of expectations by investigating the link between political climate and the pricing of sovereign debt. The literature on sovereign risk traditionally holds that fundamental factors are key to determining the levels of sovereign bond spreads. We follow Liu (2014), who challenges this view by providing evidence that textual sentiment from news plays a role in the pricing of sovereign debt.

More precisely, we examine the relationship between the Italian political climate, defined as the aggregate mood and opinion about the Italian government, and the pricing of Italian long-run sovereign debt. We focus on Italy because of a large consensus among scholars in a number of different fields that Italy's social, political and economic organization is particularly unstable. Despite the scholarly agreement about these aspects of Italian society, no study has yet investigated in depth the role of Italy's political climate on the pricing of its sovereign debt. Considering the context of Italy together with Liu's challenge to traditional determinants of sovereign bond spreads, we ask: can changes in Italy's political climate predict changes in Italy's 10-year sovereign bond spread?

The challenge here is to measure Italy's political climate. We use web scraping techniques to collect Twitter data. We gather 140,000 English tweets dating from January 2010 to December 2017 that mention the Italian government. We then extract Italy's political climate from these tweets by performing a sentiment analysis on their text. Sentiment analysis allows us to classify the text as having a positive, negative, or neutral tone. In our analysis, we use a dictionary-based approach in which we match the words of our tweets with a general list of positive and negative words from the Harvard-IV dictionary. For each tweet, we compute a polarity index: the difference in the number of positive and negative words divided by the total number of words that composed the tweet. The polarity index spans from -1 to 1, a positive value being associated with a positive sentiment. We then aggregate these indices on a monthly basis, computing the standardized monthly mean.

Using an Autoregressive Distributed Lag (ARDL) model, we show that the Italian political climate is associated with short-run changes in Italian 10-year sovereign bond spreads. More precisely, a one-standard deviation increase in our Twitter Political Climate Index (TPCI) is linked to a 5.19 basis point reduction in the pricing of long-run Italian sovereign debt. We also show that including this variable significantly improves the model's predictive power.

This study is the first to use Twitter data to investigate the pricing of sovereign bonds over such a long time horizon. Our results suggest that political factors ought to be taken into account when investigating the pricing of sovereign debt. This study also shows that we can improve traditional analyses of sovereign bond spreads by using the predictive power of political climate.

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1 On Sunspot Fluctuations in Variable Capacity Utilization Models

This chapter is based on a joint research project with Frédéric Dufourt and Alain Venditti (Aix-Marseille Univ., CNRS, EHESS, Centrale Marseille, AMSE) and is based on a paper published in the Journal of Mathematical Economics (Volume 76, Issue C, pp. 80-94, 2018).

Abstract: *We investigate the extent to which standard one sector RBC models with positive externalities and variable capacity utilization can account for the large hump-shaped response of output when the model is submitted to a pure sunspot shock. We refine the Benhabib and Wen (2004) model considering a general type of additive separable preferences and a general production function. We provide a detailed theoretical analysis of local stabilities and local bifurcations as a function of various structural parameters. We show that, when labor is infinitely elastic, local indeterminacy occurs through Flip and Hopf bifurcations for a large set of values for the elasticity of intertemporal substitution in consumption, the degree of increasing returns to scale and the elasticity of capital-labor substitution. Finally, we provide a detailed quantitative assessment of the model and conclude with mixed results. We show that although the model is able theoretically to generate a hump-shaped dynamics of output following an i.i.d. sunspot shock under realistic parameter values, the hump is too persistent for the model to be considered fully satisfactory from an empirical point of view.*

1.1 Introduction

In this chapter, we emphasize the link between demand shocks and expectation-driven fluctuations based on the existence of sunspot equilibria. More precisely, we investigate the extent to which standard one-sector sunspot models with positive externalities and variable capacity utilization can account for "boom-bust cycles" characterized by procyclical covariations of most macroeconomic variables and a hump-shaped output response when the model is submitted to a pure sunspot shock.

The traditional view put forward in the DSGE literature is that fluctuations are triggered by shocks on economic fundamentals. However, since Cass and Shell (1983), a field of economic research has been developed to analyze the role of agents' expectations in the understanding of macroeconomic fluctuations. In particular, researchers have highlighted the fact that agents can collectively change their expectations due to exogenous reasons, not necessarily related to economic fundamentals. In turn, these changes in expectations generate fluctuations which validate ex-post the initial expectations and are thus consistent with rational expectations, i.e. sunspot fluctuations are based on self-fulfilling prophecies.

The first sunspot model using the framework of the RBC/DSGE literature (Benhabib and Farmer, 1994) was shown to perform as well as, or even better than, the canonical RBC model (Farmer and Guo, 1994). However, a major hurdle this literature faced was that the existence of sunspot equilibria required very large levels of increasing returns to scale, inconsistently with the data. This weakness was considered one of the main challenge for the macroeconomic sunspot literature until Wen (1998) proposed a simple extension consisting in introducing a variable capital utilization rate in the Benhabib-Farmer setup, in the spirit of Greenwood, Hercowitz, and Huffman (1988).[1] It was shown that this simple extension to the canonical one-sector model was sufficient to allow for the existence of sunspot fluctuations under low and empirically plausible levels of increasing returns. Moreover, Benhabib and Wen (2004) showed that this model could also explain many dimensions of observed

[1] An alternative explanation is to introduce a two-sector setup with increasing returns affecting mostly the investment good sector. See Dufourt, Nishimura, and Venditti (2015).

business cycles when the model is submitted to correlated fundamental and sunspot shocks. In particular, the model is able to account for Pigou cycles: periods of booms and busts triggered by exogenous changes in agents' expectations and affecting most macroeconomic variables. The Benhabib-Wen (henceafter BW) model then put an end to years of discussions about the credibility of sunspot models and their ability to explain salient features of observed business cycles.

Yet, a careful examination of the results presented by BW reveals that there remains one dimension for which the model is not entirely satisfactory. While a positive sunspot shock does generate procyclical movements in consumption, hours worked, investment and output – consistently with the data – these impulse responses are not *hump-shaped*. This is problematic since, starting with the seminal analysis of Blanchard and Quah (1989), there exists a bulk of empirical literature showing that the typical impulse response of output to a properly defined (through various assumptions) "demand shock" is hump-shaped. Clearly, for an explanation of actual business cycles based on sunspot/self-fulfilling prophecies to be fully convincing, these models should be able to replicate all the main stylized facts associated with a canonical demand shock identified in the empirical literature.

The aim of this chapter is thus twofold. First, we observe that in the initial BW model, very tight restrictions on the specification of preferences and on the production side of the economy are considered. These restrictions imply in turn very specific values for some crucial economic parameters that are known to affect not only the local stability properties of the models, but also their business cycle properties: the elasticity of intertemporal substitution (EIS) in consumption, the degree of increasing returns to scale (IRS), the wage-elasticity of labor supply, and the capital-labor elasticity of substitution in production. From a theoretical point of view, it is thus important to assess whether the result that indeterminacy can occur under low degrees of increasing returns to scale in the BW setup is robust when we consider the whole range of empirically credible values for these parameters. As a result, we provide in the first part of the chapter a complete analysis of the local stability properties of the model as a function of these various economic parameters.

Second, based on the whole picture of the ranges of values for which the model is locally indeterminate, we assess whether the inability of the BW model to replicate a hump-shaped output dynamics in response to a pure sunspot shock is *robust* – i.e., structural to the model – or if it is due to the fact that this model was evaluated under too strong restrictions regarding the specifications of individual preferences and the production function.

Our main findings can be summarized as follows. First, we prove that, under the class of general additively separable preferences and a general production function, local indeterminacy occurs through Flip and Hopf bifurcations for a large set of values for the degree of IRS, the EIS in consumption and the capital-labor elasticity of substitution, provided that the labor supply elasticity is large. In particular, the degree of IRS can be made arbitrarily small when the other parameters are in an appropriate range. Likewise, indeterminacy can occur for a range of values for the capital-labor elasticity of substitution that extends well beyond one – including, when the degree of IRS is not too large, the case a perfect factor complementarity. Second, we perform a quantitative analysis of the model directed toward the ability to replicate a hump-shaped dynamics of output in response to a pure sunspot shock. We show that, from a theoretical point of view, a standard one-sector model with variable capacity utilization in the spirit of BW *is able* to reproduce such a hump-shaped dynamics, while maintaining the procyclicality of all the main macroeconomic variables along the business cycle (boom-bust cycles). The key ingredients for obtaining this result are to consider a value for EIS in consumption in the upper range of available empirical estimates, a quite substantial increase in the degree of factor substitutability compared to the Cobb-Douglas production function, and a slightly larger degree of IRS than considered in the BW model. On the other hand, we also show that the obtained hump-shaped dynamics is too persistent to be considered entirely consistent with observed data, leading us to conclude that the puzzle is improved but not entirely solved.

The remaining of this chapter is organized as follows. We present a generalized version of the one-sector model with variable capital utilization rate in section 1.2, as well as the corresponding intertemporal equilibrium and steady state. We derive the local stability properties and local bifurcations in section 1.3. In section 1.4 we discuss the ability of our model to account for the stylized facts associated with a canonical demand shock when the source of the business cycle is a pure sunspot shock. We also check the robustness of our results considering extended formulations with habit formation in consumption or dynamic learning by doing in production. We conclude in section 1.5.

1.2 The Model

We consider a closed economy framework in the spirit of Wen (1998) and Benhabib and Wen (2004). The economy is composed of a large number of identical infinitely-lived agents and a large number of identical producers. Agents consume, supply labor and accumulate capital subject to a variable capacity utilization rate that also influences the depreciation rate of capital. Firms produce the unique final good which can be used either for consumption or investment. All markets are perfectly competitive, but there are externalities in production.

1.2.1 The Production Structure

The production sector is composed of a large number of identical firms which operate under perfect competition. Output Y_t is produced by combining labor L_t and capital services $u_t K_t$, where u_t is the capital utilization rate. The technology of each firm exhibits constant returns to scale with respect to its own inputs and we consider that knowledge diffusion occurs, in the sense that each of the many firms benefits from positive externalities due to the contribution of the average level of labor $\bar{L}$ and capital services $\bar{u}\bar{K}$. These external effects are exogenous and not traded in markets. The production function is

$$Y_t = Af(u_t K_t, L_t)e(\bar{u}_t \bar{K}_t, \bar{L}_t) \tag{1.1}$$

where $A > 0$ is a scaling technology parameter and $e(\bar{u}_t \bar{K}_t, \bar{L}_t)$ is the externality variable. Our first departure from BW is that we do not restrict the production function to be Cobb-Douglas. Rather, our production function is general and satisfies:

Assumption 1.. *$f(uK, L)$ is $\mathbf{C}^2$ over $\mathbb{R}^2_{++}$, increasing in (uK, L), concave over $\mathbb{R}^2_{++}$ and homogeneous of degree one. $e(\bar{u}\bar{K}, \bar{L})$ is $\mathbf{C}^1$ over $\mathbb{R}_{++}$ and increasing in $(\bar{u}\bar{K}, \bar{L})$.*

Firms rent effective capital units at the real rental rate r_t and hire labor at the unit real wage w_t. The profit maximization program of the firm,

$$\max_{\{Y_t, L_t, u_t K_t\}} Y_t - w_t L_t - r_t u_t K_t,$$

leads to the standard demand function for effective capital $u_t K_t$ and labor L_t:

$$r_t = A f_1(u_t K_t, L_t) e(\bar{u}_t \bar{K}_t, \bar{L}_t) \tag{1.2}$$

$$w_t = A f_2(u_t K_t, L_t) e(\bar{u}_t \bar{K}_t, \bar{L}_t) \tag{1.3}$$

We can compute the share of capital in total income $s(uK, L)$, the elasticity of capital-labor substitution $\sigma(uK, L)$ and the elasticities of the externality variable with respect to labor $\varepsilon_{eL}(\bar{u}\bar{K}, \bar{L})$ and capital $\varepsilon_{eK}(\bar{u}\bar{K}, \bar{L})$:

$$s(uK, L) = \frac{uKf_1(uK,L)}{f(uK,L)} \in (0, 1), \quad \sigma(uK, L) = -\frac{(1-s(uK,L))f_1(uK,L)}{uKf_{11}(uK,L)} > 0 \tag{1.4}$$

$$\varepsilon_{eK}(\bar{u}\bar{K}, \bar{L}) = \frac{e_1(\bar{u}\bar{K},\bar{L})\bar{K}}{e(\bar{u}\bar{K},\bar{L})}, \quad \varepsilon_{eL}(\bar{u}\bar{K}, \bar{L}) = \frac{e_2(\bar{u}\bar{K},\bar{L})\bar{L}}{e(\bar{u}\bar{K},\bar{L})} \tag{1.5}$$

It can be noted that the choice of a Cobb-Douglas production function, as in BW, implies $\sigma(uK, L) = 1$ whereas the use of a general production function entails $\sigma(uK, L) \in (0, +\infty)$. To simplify notation, we now denote by $s, \sigma, \varepsilon_{eK}$ and ε_{eL} the corresponding elasticities evaluated at the steady-state. In order to allow for a direct comparison with BW, we also introduce the following assumption on externalities

Assumption 2.. *The externalities satisfy $\varepsilon_{eK} = s\Theta$ and $\varepsilon_{eL} = (1 - s)\Theta$ with $\Theta > 0$ the level of increasing returns.*

In this case, we get indeed $\varepsilon_{eK} + \varepsilon_{eL} = \Theta$, as assumed in BW.

1.2.2 Households

There exists a continuum of mass 1 of identical households maximizing their expected lifetime utility subject to a capital accumulation constraint. The representative household supplies elastically an amount of labor $l \in [0, \ell]$ at each period, with $\ell > 1$ its endowment of labor. It derives utility from consumption c and leisure $\mathcal{L} = \ell - l$ according to an additively separable instantaneous utility function

$$U(c, \mathcal{L}) = u(c) + Bv(\mathcal{L})$$

where $B > 0$ is a scaling parameter, which satisfies:

Assumption 3.. *$u(c)$ and $v(\mathcal{L})$ are respectively $\mathbf{C}^2$ over $\mathbb{R}_+$ and $[0, \ell]$, increasing and concave. Moreover, $\lim_{x\to 0} v'(x)x = +\infty$ and $\lim_{x\to+\infty} v'(x)x = 0$, or $\lim_{x\to 0} v'(x)x = 0$ and $\lim_{x\to+\infty} v'(x)x = +\infty$.*[2]

We also introduce the intertemporal elasticity of substitution in consumption and the elasticity of labor supply with respect to wage:

$$\varepsilon_{cc}(c) = -\frac{u'(c)}{u''(c)c}, \quad \varepsilon_{lw}(l) = -\frac{v'(\mathcal{L})}{v''(\mathcal{L})l} \tag{1.6}$$

Our utility function generalizes the one considered by BW, since they impose a logarithmic consumption specification associated with a unitary elasticity of intertemporal substitution (EIS) in consumption $\varepsilon_{cc}(c) = -u'(c)/(u''(c)c) = 1$, and a linear specification with respect to leisure implying an infinitely-elastic labor supply with $\varepsilon_{lw}(l) = +\infty$. Our more general assumptions enable us to consider the whole range of positive values for both of these elasticities.

The capital stock k_t is owned and accumulated by households and the utilization rate of capital, u_t, is an endogenous variable. Households rent capital services $u_t k_t$ to firms at the real rental rate r_t. Increasing the utilization rate thus increases the services of capital but it also has a direct impact on the depreciation rate of capital. The latter is a convex function of

[2]If $v(x) = x^{1-\chi}/(1-\chi)$ with $\chi \geq 0$ the inverse of the elasticity of labor, the first part of the boundary conditions is satisfied when $\chi > 1$ while the second part holds if $\chi \in [0, 1)$.

the utilization rate, such that

$$\delta_t = \frac{u_t^\gamma}{\gamma} \in (0,1), \text{ with } \gamma > 1 \tag{1.7}$$

The capital accumulation equation constraint can now be written as follows:

$$k_{t+1} = (1-\delta_t)k_t + w_t l_t + r_t u_t k_t - c_t \tag{1.8}$$

with k_0 given.

Combing (1.7) and (1.8), the consumer thus solves the following lifetime utility maximization program (where $\beta \in (0,1)$ is the discount factor)

$$\begin{aligned} \max_{\{c_t, k_{t+1}, l_t, u_t\}_{t=0\ldots\infty}} \quad & E_0 \sum_{t=0}^{+\infty} \beta^t \left[u(c_t) + Bv(\ell - l_t)\right] \\ s.t. \quad & k_{t+1} = \left(1 - \frac{u_t^\gamma}{\gamma}\right) k_t + w_t l_t + r_t u_t k_t - c_t \\ & k_0 \text{ given} \end{aligned} \tag{1.9}$$

The first-order conditions for an interior solution can be written as

$$Bv'(\ell - l_t) = w_t u'(c_t) \tag{1.10}$$

$$u'(c_t) = \beta E_t R_{t+1} u'(c_{t+1}) \tag{1.11}$$

$$r_t = u_t^{\gamma-1} \tag{1.12}$$

where $R_t = 1 - \delta_t + r_t u_t$ is the net return factor on capital. An optimal path must also satisfy the transversality condition:

$$\lim_{t\to+\infty} E_0 \beta^t u'(c_t) k_{t+1} = 0 \tag{1.13}$$

Equation (1.10) is the consumption-leisure trade-off equation, (1.11) is the con-sumption-saving arbitrage equation (i.e., the Euler equation), and (1.12) determines the optimal utilization rate of capital.

1.2.3 General Equilibrium

A symmetric general equilibrium is a sequence of prices $\{w_t, r_t\}$ and quantities such that all markets clear, $L_t = l_t$ and $K_t = k_t$ for any t, and the externality variable satisfies $(\overline{u}_t\overline{K}_t, \overline{L}_t) = (u_tK_t, L_t)$.

It is easy to use some of the equilibrium conditions to reduce the dynamic system defining a general equilibrium to its minimal dimension. We can first observe that combining (1.2) with (1.12) gives u_t as a function of capital and labor, namely $u_t = \nu(k_t, l_t)$. Similarly, we can derive a consumption demand function $c(k_t, l_t)$ by implicitly solving the consumption-leisure trade-off equation (1.10) with respect to c_t. Finally, from the capital accumulation equation (1.8) and the Euler equation (1.11), we can derive that a general equilibrium of this economy is a sequence $\{k_t, l_t\}$ satisfying the following two-dimensional system of differential equations in k and l:

$$\begin{aligned} Af(\nu(k_t, l_t)k_t, l_t)e(\nu(k_t, l_t)k_t, l_t) + (1-\delta_t)k_t - c(k_t, l_t) - k_{t+1} &= 0 \\ \beta E_t R_{t+1} u'(c(k_{t+1}, l_{t+1})) - u'(c(k_t, l_t)) &= 0 \end{aligned} \tag{1.14}$$

with $\delta_t = \nu(k_t, l_t)^\gamma/\gamma$ and $R_t = 1 - \delta_t + Af_1(\nu(k_t, l_t)k_t, l_t)\nu(k_t, l_t)e(\nu(k_t, l_t)k_t, l_t)$.

Definition 1.. *An intertemporal equilibrium is a path $\{k_t, l_t\}_{t\geq 0}$, with $(k_t, l_t) \in \mathbb{R}_{++} \times (0, \ell)$ and $k_0 > 0$, that satisfies equations (1.14) and the transversality condition (1.13).*

1.2.4 Normalized Steady State and Linearization

A steady state is a 4-uple (k^*, l^*, u^*, c^*) such that:

$$\begin{aligned} & Af_1(u^*k^*, l^*)u^*e(u^*k^*, l^*) = \tfrac{1-\beta(1-\delta^*)}{\beta} \equiv \tfrac{\theta}{\beta} \\ & Af_1(u^*k^*, l^*)u^*e(u^*k^*, l^*) = u^{*\gamma-1} \\ & c^* = Af(u^*k^*, l^*)e(u^*k^*, l^*) - \delta^*k^* \\ & Bv'(\ell - l^*) = Af_2(u^*K^*, l^*)e(u^*K^*, l^*)u'(c^*) \end{aligned} \tag{1.15}$$

with $\delta^* = u^{*\gamma}/\gamma$. Considering the rental rate as defined by (1.2) together with equations (1.11) and (1.12) evaluated at the steady state, we derive the explicit value of u^* as

$$u^* = \left(\frac{\gamma(1-\beta)}{\beta(\gamma-1)}\right)^{1/\gamma} \tag{1.16}$$

We conclude from this expression that $\delta^* = (1-\beta)/[\beta(\gamma-1)]$. Equivalently, if δ is calibrated, the corresponding value for γ is $\gamma^* = [1-\beta(1-\delta)]/(\beta\delta)$. We can also use the scaling parameters A and B in order to give conditions for the existence of a normalized steady state (NSS in the sequel) which remains invariant to parameter changes, for example a NSS such that $k^* = l^* = 1$.

Proposition 1.. *Under Assumptions 1-3, there exist $A^*, B^* > 0$ such that when $A = A^*$ and $B = B^*$, a NSS satisfying $(k^*, l^*, c^*) = (1, 1, (\theta - s\beta\delta^*)/s\beta)$ is the unique solution of (1.15).*

Proof. See Appendix A.1.

□

Using a continuity argument we derive from Proposition 1 that there exists an intertemporal equilibrium for any k_0 in the neighborhood of k^*. In the rest of the chapter, we evaluate all the shares and elasticities previously defined at the NSS. From (1.4) and (1.5), we consider indeed $s(u^*, 1) = s$, $\sigma(u^*, 1) = \sigma$, $\varepsilon_{eK}(u^*, 1) = \varepsilon_{eK}$, $\varepsilon_{eL}(u^*, 1) = \varepsilon_{eL}$, $\varepsilon_{cc}(c^*) = \varepsilon_{cc}$ and $\varepsilon_{lw}(1) = \varepsilon_{lw}$.

Finally, we log-linearize the model in order to analyze the local dynamics around the NSS for different values of four crucial parameters which are the intertemporal elasticity of substitution in consumption ε_{cc}, the elasticity of the labor supply ε_{lw}, the elasticity of capital-labor substitution σ and the degree of increasing returns to scale Θ. In what follows, we provide a detailed theoretical analysis of local stabilities and local bifurcations as function of these crucial parameters.

1.3 Local Stability and Bifurcation Analysis

Our model is composed of one forward looking variable, hours worked, and one predetermined variable, the capital stock, i.e. (1.14) is two-dimensional. Since time is discrete, one can use the geometrical method developed by Grandmont, Pintus, and De Vilder (1998) to study the local stability properties of our normalized steady state, as well as the emergence of local bifurcations.

Lemma 1.. *Under Assumptions 1-3, the characteristic polynomial is*

$$P(\lambda) = \lambda^2 - \lambda\mathcal{T} + \mathcal{D} \tag{1.17}$$

with

$$\begin{aligned}
\mathcal{D} &= \tfrac{1}{\beta}\left[1 + \frac{\Theta\theta(\gamma-1)\left(1+\frac{\sigma}{\varepsilon_{lw}}\right)}{(\gamma-1)[\theta(1-s)+s]+\frac{1}{\varepsilon_{lw}}[\sigma(\gamma-1)+1-s]-\Theta\left[1+\sigma(1-s)(\gamma-1)\beta(1-\delta)+\frac{s\sigma}{\varepsilon_{lw}}\right]}\right]\\
\mathcal{T} &= 1+\mathcal{D}+\frac{\theta(\gamma-1)}{\beta s}\,\frac{(\theta-\beta\delta s)(1-s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)-\Theta\left[\varepsilon_{cc}(\theta-\beta\delta s)\left(1+\frac{s\sigma}{\varepsilon_{lw}}\right)-(1-s)(\theta-\sigma\beta\delta s)\right]}{(\gamma-1)[\theta(1-s)+s]+\frac{1}{\varepsilon_{lw}}[\sigma(\gamma-1)+1-s]-\Theta\left[1+\sigma(1-s)(\gamma-1)\beta(1-\delta)+\frac{s\sigma}{\varepsilon_{lw}}\right]}
\end{aligned} \tag{1.18}$$

Proof. See Appendix A.2.

□

We study the variation of the Trace $\mathcal{T}$ and Determinant $\mathcal{D}$ when one of our parameter of interest is made to vary continuously in its admissible range. To avoid considering a large number of cases that are not relevant empirically, we restrict the possible values of the amount of increasing returns Θ, and we also introduce some specific parametric values for δ, β and s which are consistent with quarterly US data:

Assumption 4.. $\delta = 0.025$, $\beta = 0.99$, $s \in (0.25, 0.35)$ *and* $\Theta \leq \Theta^{max} = \min\{(1 - s)/s\sigma, 0.42\}$.[3]

We derive from these parametric restrictions the following property:

[3] The values for δ and β are almost universally shared in the RBC/DSGE literature, together with a capital share around 0.3. The restriction on the size of externalities Θ is based on the estimated degree of aggregate IRS for the US economy by Basu and Fernald (1997) and ensures that the labor demand function has a standard negative slope.

Lemma 2.. *Under Assumptions 1-4, $\partial\mathcal{D}/\partial\varepsilon_{lw} > 0$, $\lim_{\varepsilon_{lw}\to 0}\mathcal{D} > 1$ and $\mathcal{D} < 1$ if and only if*

$$\Theta > \underline{\Theta} \equiv \frac{(\gamma-1)[\theta(1-s)+s]}{1+\sigma(1-s)(\gamma-1)\beta(1-\delta)} \in (0, \Theta^{max}) \tag{1.19}$$

and

$$\varepsilon_{\ell w} > \hat{\varepsilon}_{\ell w} \equiv \frac{\sigma(\gamma-1)+1-s-\Theta\sigma s}{[1+\sigma(1-s)(\gamma-1)\beta(1-\delta)](\Theta-\underline{\Theta})}$$

Proof. See Appendix A.3.

□

As is usual in the sunspot literature, a large enough amount of IRS and a large enough elasticity of labor are required to get a locally indeterminate steady state. From now on, we then introduce these lower bound restrictions on Θ and $\varepsilon_{\ell w}$, together with some upper bound on the EIS ε_{cc} in order to simplify the analysis without loss of generality.

Assumption 5.. $\Theta > \underline{\Theta}$, $\varepsilon_{lw} > \hat{\varepsilon}_{\ell w}$ *and* $\epsilon_{cc} \leq \bar{\varepsilon}_{cc} \equiv \frac{\frac{1-s}{\Theta^{max}}+\frac{\theta(1-s)}{\theta-\beta\delta s}}{1+\frac{1-s}{\Theta^{max}\varepsilon_{lw}}}$.[4]

In this analysis of local stability and local bifurcation, we choose the elasticity of capital-labor substitution σ to be our bifurcation parameter. As discussed in Section 2.1, $\sigma \in (0,\infty)$. In order to derive the local stability properties of the steady state, we consider the locus of points $(\mathcal{T}(\sigma), \mathcal{D}(\sigma))$ as σ is made to vary continuously in $(0,\infty)$. One can indeed define a line denoted Δ_σ as follows : $\mathcal{D} = \Delta_\sigma(\mathcal{T}) = \mathcal{S}\mathcal{T} + \mathcal{C}$, which is independent of σ. The slope of the latter, S, is the ratio of the partial derivatives of the $\mathcal{D}$eterminant and $\mathcal{T}$race with respect to σ.[5] Obvious computations show that $\mathcal{D}'(\sigma) > 0$ and, under Assumptions 4 and 5, $\mathcal{T}'(\sigma) > 0$, so that $\mathcal{S} = \mathcal{D}'(\sigma)/\mathcal{T}'(\sigma) > 0$.

Locating the line Δ_σ in the $(\mathcal{T}$,$\mathcal{D})$ plan allows to provide a full stability and bifurcation analysis. Indeed all configurations are described trough the consideration of three lines. On the one hand, an (AC) line is associated with an eigenvalue of the Jacobian matrix which is equal to one when $P(1) = 0$. On the other hand, an (AB) line is associated with an

[4]Our restriction on the EIS in consumption implies $\bar{\epsilon}_{cc} \in (2.41, 2.698)$, so that, depending on the value of the elasticity of labor, we consider the whole range of empirical estimates we have found for this parameter (see among others Campbell 1999, Kocherlakota et al. 1996, Mulligan 2002, Vissing-Jørgensen and Attanasio 2003, and Gruber 2013, who obtained estimates ranging between 0 and 2.3).

[5] We orient the reader to Grandmont et al. (1998) for a detailed presentation of the method.

eigenvalue equal to minus one when $P(-1) = 0$. Moreover, a segment [BC] is associated with two eigenvalues which are complex conjugates and have modulus equal to one when $\mathcal{D} = 1$ and $\mathcal{T} \in (-2, 2)$. As a result, the steady state is a *saddle-point* when $P(1) < 0 (> 0)$ and $P(-1) > 0 (< 0)$. Also, the steady state is a *sink* when $P(1) > 0$, $P(-1) > 0$ and $\mathcal{D} < 1$. In other words, the dynamics is locally *indeterminate* in the triangle ABC. Finally, in all other cases, the steady state is a *source*.

We show in Appendix A.1 that beside the lower bound $\underline{\Theta}$ as defined in Lemma 2, there exists an upper bound $\hat{\Theta} \in (\underline{\Theta}, \Theta^{max})$ for the level of IRS which leads to two different types of locations for the Δ_σ line. This critical value is defined as follows

$$\hat{\Theta} \equiv \frac{2s(1+\beta)\left\{(\gamma-1)[\theta(1-s)+s]+\frac{1-s}{\varepsilon_{lw}}\right\}+\theta(\gamma-1)(1-s)(\theta-\beta\delta s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)}{2s[1+\beta-\theta(\gamma-1)]+\theta(\gamma-1)[\varepsilon_{cc}(\theta-\beta\delta s)-(1-s)\theta]} \tag{1.20}$$

It can be proved that when $\Theta \in [0, \underline{\Theta})$ the steady state is always saddle-point stable while we get the following geometric configurations when $\Theta > \underline{\Theta}$.

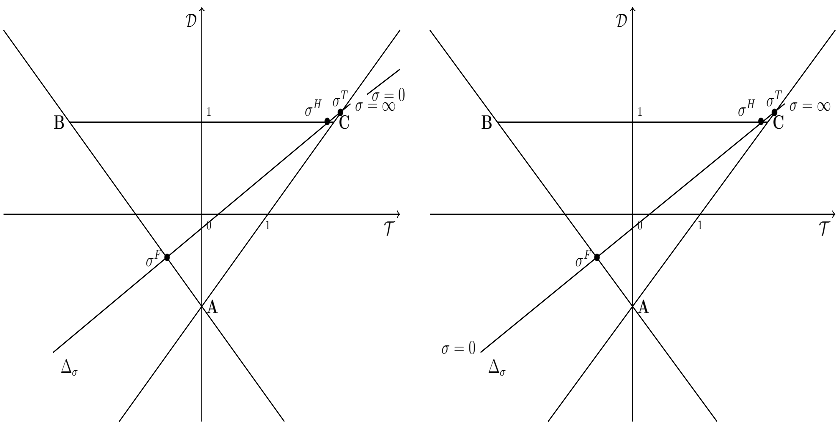


Figure 1.1 – Local Determinacy for Low Values of Increasing Returns to Scale.

Figure 1.1 depicts the case where $\Theta \in (\underline{\Theta}, \hat{\Theta})$. When $\sigma = 0$, the dynamics is locally determinate. As σ increases, the dynamics remains locally determinate until $\sigma = \sigma^F$. At this value, a Flip bifurcation occurs and the dynamics becomes locally indeterminate. As the Δ_σ line crosses the triangle ABC, the steady state is a sink until $\sigma = \sigma^H$. At this value, the two eigenvalues of our system of differential equations are complex conjugates with a modulus equal to one and a Hopf bifurcation occurs. Between σ^H and σ^T , the local dynamics is unstable. One can note that a transcritical bifurcation occurs when $\sigma = \sigma^T$ which can lead to the apparition of multiple steady states. Finally, when $\sigma \to \infty$, the dynamics is again locally determinate. Local indeterminacy thus occurs through a Flip and a Hopf bifurcation.

Figure 1.2 depicts the case where $\Theta > \hat{\Theta}$. The main difference with the previous case is that the locus $(T(0), D(0))$ is now in the triangle ABC. We also prove in Appendix A.1 that we need to introduce a second bound $\bar{\Theta} \leq \Theta^{max}$ to guarantee the existence of local indeterminacy through a Hopf bifurcation. We then get basically the same conclusions as in the case $\Theta \in (\underline{\Theta}, \hat{\Theta})$ except that now there is no more any flip bifurcation.

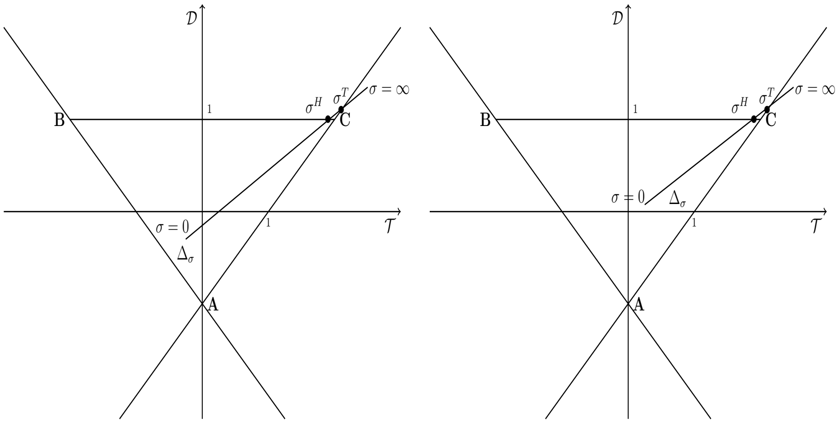


Figure 1.2 – Local Determinacy for Large Values of Increasing Returns to Scale.

We then reach the following Proposition:

Proposition 2.. *Let Assumptions 1-4 hold and consider the bound $\underline{\Theta}$ as given by (1.19). Then, when $\Theta \in [0, \underline{\Theta})$, the steady state is a saddle-point. Under the additional Assumption 5, let us consider the bound $\hat{\Theta}$ as given by (1.20). Then there exist $\bar{\Theta} \in (\hat{\Theta}, \Theta^{max}]$, $\tilde{\varepsilon}_{\ell w} > 0$ and $0 \leq \sigma^F < \sigma^H < \sigma^T < +\infty$ such that when $\varepsilon_{\ell w} > \max\{\tilde{\varepsilon}_{\ell w}, \hat{\varepsilon}_{\ell w}\}$, the following results hold:*

(i) If $\Theta \in (\underline{\Theta}, \hat{\Theta})$, the steady state is

- *a saddle-point when $\sigma \in (0, \sigma^F)$,*
- *a sink, when $\sigma \in (\sigma^F, \sigma^H)$,*
- *a source when $\sigma \in (\sigma^H, \sigma^T)$,*
- *a saddle-point when $\sigma \in (\sigma^T, \infty)$.*

(ii) If $\Theta \in (\hat{\Theta}, \bar{\Theta})$, the steady state is

- *a sink when $\sigma \in (0, \sigma^H)$,*

– *a source when* $\sigma \in (\sigma^H, \sigma^T)$,

– *a saddle-point when* $\sigma \in (\sigma^T, \infty)$.

The lower bound $\tilde{\varepsilon}_{\ell w}$ *and the Hopf, flip and transcritical bifurcation values are respectively defined as:*

$$
\begin{aligned}
\tilde{\varepsilon}_{\ell w} &\equiv \frac{\gamma-1+\Theta\frac{\theta-\beta\delta s}{\beta\delta}}{\Theta(1-s)(\gamma-1)\beta(1-\delta)},\\
\sigma^H &\equiv \frac{(1-\beta)\left[(\gamma-1)[\theta(1-s)+s]+\frac{1-s}{\varepsilon_{lw}}\right]-\Theta[1-\beta-\theta(\gamma-1)]}{(1-\beta)\left\{\Theta\left[(\gamma-1)(1-s)\beta(1-\delta)-\frac{\theta-\beta\delta s}{\varepsilon_{lw}\beta\delta}\right]-\frac{\gamma-1}{\varepsilon_{lw}}\right\}},\\
\sigma^F &\equiv \frac{\{2s[1+\beta-\theta(\gamma-1)]+\theta(\gamma-1)[\varepsilon_{cc}(\theta-\beta\delta s)-\theta(1-s)]\}(\hat{\Theta}-\Theta)}{s\left\{2(1+\beta)\left[\Theta\left[(\gamma-1)(1-s)\beta(1-\delta)+\frac{s}{\varepsilon_{lw}}\right]-\frac{\gamma-1}{\varepsilon_{lw}}\right]+\Theta\theta(\gamma-1)\left[(1-s)\beta\delta-\frac{2}{\varepsilon_{lw}}+\frac{\varepsilon_{cc}(\theta-\beta\delta s)}{\varepsilon_{lw}}\right]\right\}},\\
\sigma^T &\equiv \frac{(\theta-\beta\delta s)(1-s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)-\Theta[\varepsilon_{cc}(\theta-\beta\delta s)-(1-s)\theta]}{\Theta s\left[\beta\delta(1-s)+\frac{\varepsilon_{cc}(\theta-\beta\delta s)}{\varepsilon_{lw}}\right]}.
\end{aligned}
$$

Proof. See Appendix A.4.

□

From Proposition 2, we clearly recover the standard result that multiple equilibrium paths are ruled out when the amount of IRS is small enough with $\Theta \in [0, \underline{\Theta})$. When the degree of increasing returns to scale is positive but not too large, $\Theta \in (\underline{\Theta}, \hat{\Theta})$, there is a minimal amount of capital-labor substitution σ^F which is necessary to get local indeterminacy and sunspot fluctuations. As the degree of IRS gets larger, $\Theta \in (\hat{\Theta}, \bar{\Theta})$, indeterminacy can be obtained with an arbitrarily small elasticity of substitution between capital and labor, including the case of strict factor complementarity. In all cases, however, indeterminacy is excluded when the elasticity of substitution between factors is very large. It is also worth noting that the additional bound $\tilde{\varepsilon}_{\ell w}$ on the elasticity of labor is, beside the upper bound $\bar{\Theta}$, also introduced to ensure the existence of a Hopf bifurcation. Indeed, if Assumptions 1-5 hold with $\varepsilon_{\ell w} < \tilde{\varepsilon}_{\ell w}$, the Hopf bifurcation value and the source configuration for the steady state no longer exist. The only possible transition is between the saddle-point and sink configurations through a transcritical or a Flip bifurcation.

In order to illustrate Proposition 2, and to immediately compare our results to the conclusions of BW, we assume for now an infinitely elastic labor supply with $\varepsilon_{\ell w} = +\infty$. Figure 1.3

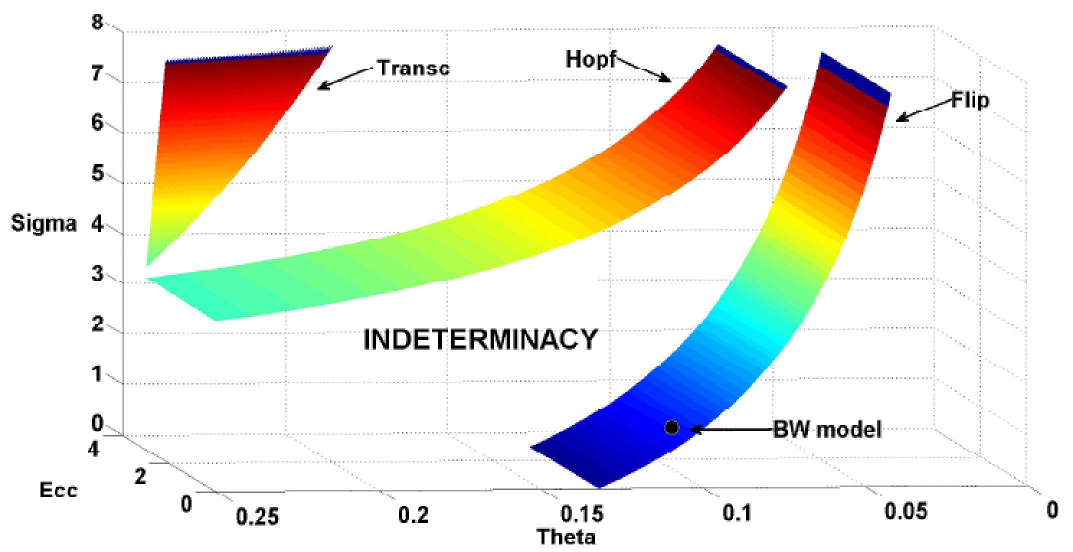


Figure 1.3 – Indeterminacy Area and Bifurcation Loci.

displays the determinacy/indeterminacy areas as well as the corresponding bifurcation loci in the 3-dimensional plane defined by ε_{cc}, Θ and σ when the standard calibration $s = 0.3$ is considered. Clearly, there exists a wide range of values for which the model is indeterminate. The BW model, associated with a unitary elasticity of intertemporal substitution ($\varepsilon_{cc} = 1$), a unitary elasticity of substitution between capital and labor ($\sigma = 1$), and a degree of increasing returns to scale close to its minimum value consistent with indeterminacy ($\Theta = 0.11$), is just a particular point in this plane which locates the model relatively "close" to the flip bifurcation locus in the parameter space. Yet, other, potentially very different, combinations of values for these parameters are also consistent with an indeterminate steady-state. A general assessment of whether the BW model with variable capacity utilization is able or not to replicate the main "stylized facts" associated with a canonical demand shock when the model is submitted to self-fulfilling changes in expectations requires to consider the whole range of values for which the model is indeterminate, provided these values are empirically credible. This is the issue to which we now turn.

1.4 Stylized Facts of Demand Shocks

1.4.1 Preliminary Considerations

In order to understand why considering alternative configurations for ε_{cc}, Θ and σ is important while keeping $\varepsilon_{\ell w} = +\infty$ as in BW, consider as a starting point the effects of increasing the elasticity of capital labor substitution σ on the dynamics of output following a positive sunspot shock. Under our benchmark calibration with $\Theta = 0.11$, we can apply the formulae in Proposition 2 to obtain that the steady-state is indeterminate for $\sigma \in (\sigma_F, \sigma_H)$ with $\sigma_F \approx 0.74$ and $\sigma_H \approx 5.84$. We thus consider four different values for σ: $\sigma = 0.8$, $\sigma = 1$, $\sigma = 2$ and $\sigma = 5.8$. Figure 1.4 displays the IRFs of output associated with a positive sunspot shock. The size of the shock is set so that the initial output response is 1%.

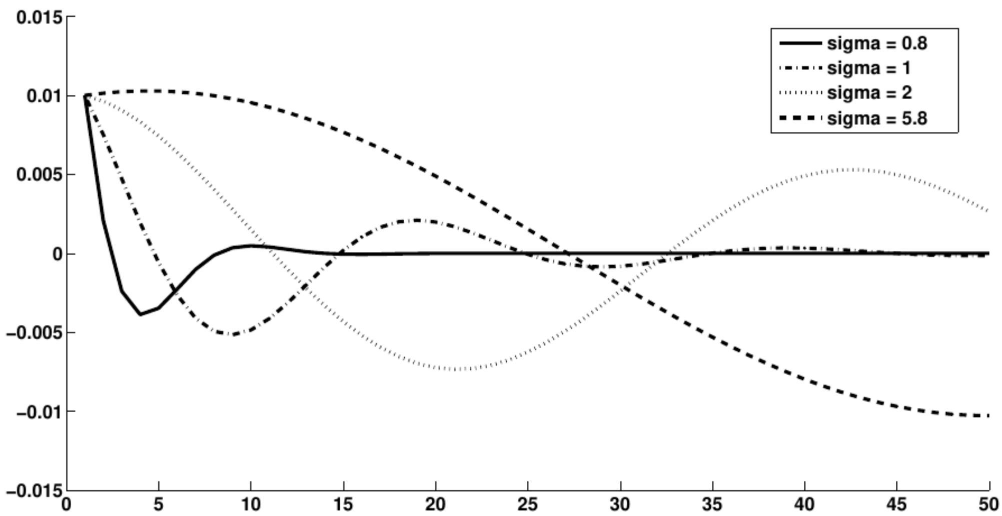


Figure 1.4 – Output Dynamics Following a Positive Sunspot Shock for Different Values of the Elasticity of Capital Labor Substitution.

As Figure 1.4 clearly illustrates, the dynamics of output is non-monotonous in all cases. Yet, when the elasticity of capital-labor substitution is small or moderate, the output response does not display the "hump" typically identified in the empirical literature. In particular, when $\sigma = 1$, we recover the inability of the BW model to account for this fact. However, Figure 4 also shows that when the elasticity of capital-labor substitution is further increased, the dynamics of output becomes more and more persistent and eventually becomes hump-shaped when σ gets close to σ_H, its maximal value consistent with indeterminacy. From a theoretical point of view, this result is important since it proves that a standard one-sector stochastic growth model with variable capacity utilization is not structurally unable to reproduce a hump-shaped dynamics of output when the model is submitted to pure (i.i.d.) sunspot shocks.

In Figure 1.5, we perform the same exercise except that, starting from the BW model with $\varepsilon_{cc} = \sigma = 1$ and $\Theta = 0.11$, we now increase the degree of increasing return to scales from $\Theta = 0.11$ to a maximal value of $\Theta = 0.4$. The same result basically obtains, albeit slightly attenuated. A hump-shaped dynamics occurs for degrees of IRS above 30%.

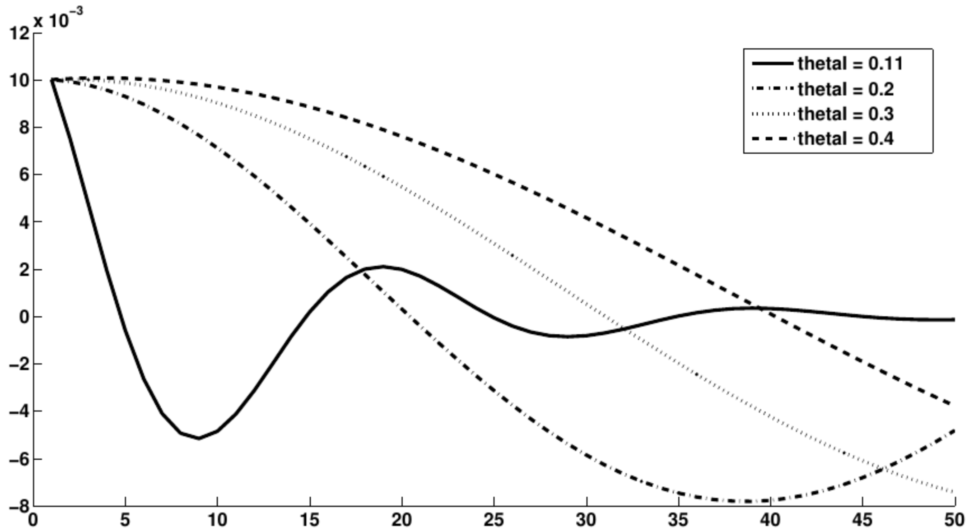


Figure 1.5 – Output Dynamics Following a Positive Sunspot Shock for Different Values of Increasing Returns to Scale.

To understand the results in Figures 1.4 and 1.5, it is useful to remind some well-known results in the theory of bifurcations. In particular, it is known that generically, when a parameter crosses its bifurcation value, there exists an invariant orbit that "surrounds" the steady-state and which influences the local dynamics of the variables. If the bifurcation is *subcritical,* this invariant orbit emerges when the steady-state is a sink. It is repelling and defines a basin of attraction within which the steady-state is locally stable. When the bifurcation is *supercritical,* the limit cycle is stable and attracts trajectories outside the steady-state.

Figure 1.6 displays this invariant orbit in the plane (k, y) when the value for σ is sufficiently close to its Hopf bifurcation value, σ^H. Interestingly, the shape of this curve is pointing to the top and to the right, suggesting that, following a sunspot shock implying that output jumps out of the steady-state, both the capital stock and output are expected to continue increasing for some periods of time. In other words, the dynamics of the model along the limit cycle is *hump-shaped*.

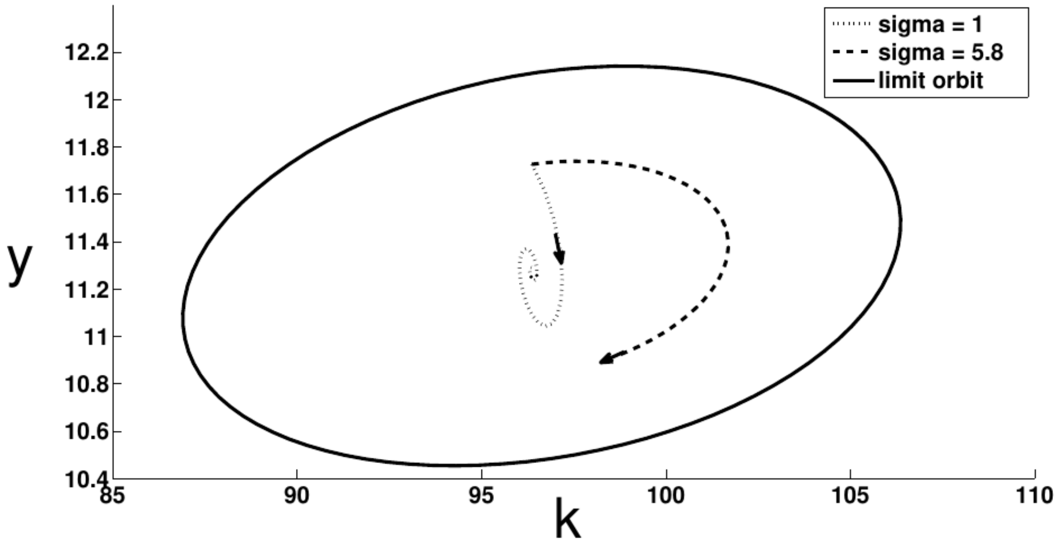


Figure 1.6 – Dynamic Trajectories and the Limit Orbit.

A general result is therefore that in order to obtain a hump-shaped dynamics of output in the variable capacity utilization model, it is sufficient to choose a calibration that locates the model sufficiently "close" to the Hopf bifurcation locus. In this case, the local dynamics of output following an i.i.d. sunspot shock will be sufficiently influenced by the limit cycle. As an illustration of this general result, we display in Figure 1.6 the dynamic trajectories associated with a 1% sunspot shock, but now the in (k, y) plane. We consider two meaningful values for σ: $\sigma = 1$, corresponding to the BW model, and $\sigma = 5.8$, a value close to the Hopf bifurcation value σ_H. The influence of the limit cycle on the dynamics is clear when σ is close to the Hopf bifurcation value.

1.4.2 Quantitative Assessment

Our examples displaying a hump-shaped dynamics were obtained by increasing either the degree of capital-labor substitution or the degree of IRS independently. In both cases, the hump was obtained for values of these parameters that were too large to be considered empirically credible (a value of 5.8 for the capital-labor elasticity of substitution or a degree of aggregate IRS greater than 30%). Yet, Figure 1.3 reveals that it is also possible to make the model closer to the Hopf bifurcation locus by *combining* a moderate increase in Θ and a moderate increase in σ. In this section, we thus perform an evaluation of the model based on what can be judged as "realistic" parameter values. Still assuming for now $\varepsilon_{\ell w} = +\infty$, we consider the most favorable configuration for which σ, Θ and ε_{cc} are set in the upper range of empirically credible estimates for these parameters. Accordingly, we fix $\Theta = 0.16$, which corresponds to the point estimate obtained by Basu and Fernald (1997) for aggregate value-added in the US economy. We allow for a substantial deviation from the Cobb-Douglas technology by increasing the capital-labor elasticity of substitution to $\sigma = 3$, consistently with the upper range of estimates for this elasticity obtained in the empirical literature.[6] Finally, although the Hopf bifurcation is independent of ε_{cc} (see proposition 2), we found that considering a large EIS in consumption helps getting a hump-shaped dynamics.[7] We thus set $\varepsilon_{cc} = 2.3$, associated with the upper range obtained by Gruber (2013).

Figure 1.7 displays the Impulse Response Functions of the main macroeconomic variables when the model is submitted to a pure sunspot shock using this configuration (DVV calibration). For comparison purposes, we also display the IRFs obtained with the BW model. We observe that the DVV model is able to explain not only "boom-bust" cycles triggered by self-fulfilling changes in expectations, but also a hump-shaped dynamics of output. The latter feature is in sharp contrast with the results obtained under the BW configuration. To under-

[6] There is no clear agreement on the size of the elasticity of capital-labor substitution σ in the empirical literature. The lower estimates belong to the range (0.4,0.9), as shown in León-Ledesma, McAdam, and Willman (2010), Klump, McAdam, and Willman (2007, 2012) and McAdam and Willman (2013). By contrast, the largest estimates obtained by Duffy and Papageorgiou (2000) and Karagiannis, Palivos, and Papageorgiou (2005) range in the interval (1.24,3.24).

[7] Changing the value of ε_{cc} actually influences the *shape* of the invariant orbit. When ε_{cc} increases, the limit cycle points more to the top, which is consistent with a hump-shaped dynamics.

stand this result, consider the system of equations (1.14) and assume that for some exogenous reason, agents expect that the rental rate of capital r_{t+1} will be high in the next period, so that R_{t+1} is also high. When the model is close to the Hopf bifurcation, agents expect that this increase in the interest rate will be much more persistent than in the BW configuration. This leads to a persistent boom in investment, associated with a large increase in the capital stock – far greater than in the BW model – and a corresponding persistent increase in the rate at which this capital stock is expected to be used.[8] An expected persistent increase in capital services in turn implies that labor demand is expected to be high for a long period of time. As a result, the representative household expects a sustained period of high real wages, leading him to increase its consumption level significantly, by a much larger extent than in the BW configuration. Since the dynamics of consumption is hump-shaped (as a result of consumption smoothing motives – a standard result in the RBC literature), a significant increase in consumption in turn implies a hump-shaped dynamics of output.

These positive results should not, however, conceal the dimensions over which the model is less satisfactory. In our view, the main deficiency of the model is that the "shape" of the hump does not really resemble the one obtained in the empirical literature estimating the macroeconomic effects of a standard demand shock. In particular, the dynamics implied by the model is not *sufficiently* hump-shaped, and it is too persistent.

1.4.3 Robustness

We now assess whether our conclusion is robust to alternative assumptions. We first depart from the infinite labor supply elasticity specification associated with Hansen (1985)'s model of indivisible individual labor supply with employment lotteries and perfect unemployment insurance that was considered up to now as in BW. We consider instead alternative calibrations regarding the aggregate labor supply elasticity that remain compatible with indeterminacy. We show that considering finite labor supply elasticities does not help to render the dynamics of output closer to the data when the model is submitted to sunspot shocks.

[8] According to (1.12), the dynamics of the utilization rate is directly related to the dynamics of r_t.

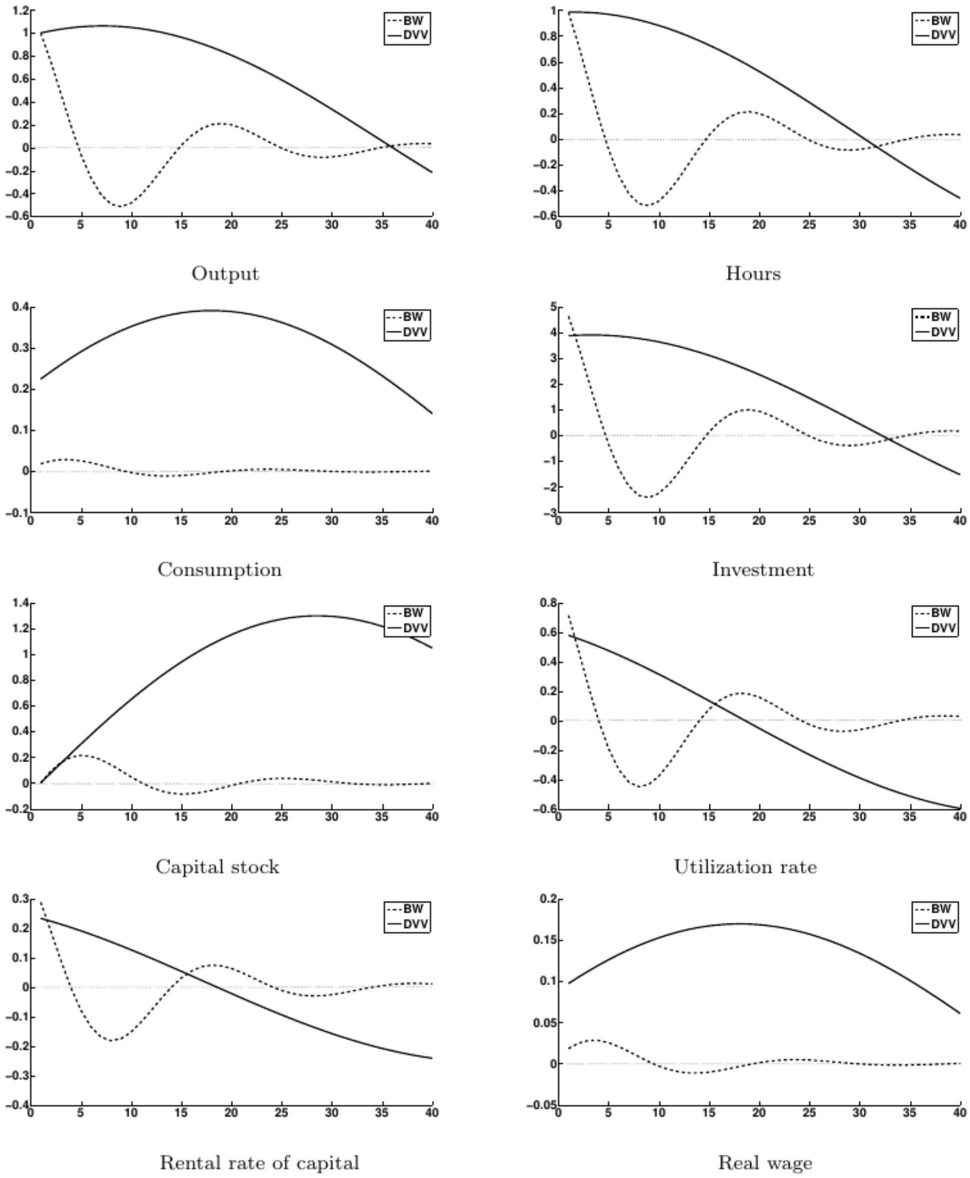


Figure 1.7 – Impulse Response Functions to a Sunspot Shock.

We then consider more significant changes to the model. Following the DSGE literature that had early emphasized that the canonical RBC model lacks endogenous propagation mechanisms (Cogley and Nason 1995, Rotemberg and Woodford 1996), we consider two of the most popular extensions proposed in the literature to enhance the dynamics of output in response to exogenous shocks: introducing habit formation in consumption, in the spirit of Boldrin, Christiano, and Fisher (2001), Jaimovich (2008) and others, and introducing a richer class of production functions associated with dynamic learning by doing, in the spirit and Chang, Gomes, and Schorfheide (2002).[9] We show that none of these extensions help to better replicate the hump-shaped dynamics of output following a sunspot shock.

1.4.3.1 Reducing Labor Supply Elasticity

As shown in Figure 1.8, decreasing the aggregate labor supply elasticity has two effects on the range of parameter values consistent with indeterminacy: first, the flip bifurcation shifts upward, implying that larger degrees of IRS are required to maintain the sink property of the steady-state. Second, the Hopf bifurcation locus also shifts upward and eventually disappears when ε_{lw} crosses a lower threshold. Quantitatively, the minimum value for Θ consistent with indeterminacy quickly increases when ε_{lw} gradually decreases. For example, when $\varepsilon_{lw} = 10$, indeterminacy requires that Θ exceeds 0.2. When $\varepsilon_{lw} = 5$, indeterminacy is already eliminated for all empirically plausible values for Θ.

Yet, it remains interesting theoretically to assess whether decreasing the aggregate labor supply elasticity could help improving the fit of the model with the data. In Figure 1.9, we thus compare the results obtained under our benchmark calibration associated with $\varepsilon_{lw} = \infty$ with those obtained under a similar calibration for all parameters except that ε_{lw} is now calibrated to $\varepsilon_{lw} = 12$, the minimum value consistent with indeterminacy. The figure clearly shows that the results are worsened under this alternative calibration. This result is easily explained by the fact that $\varepsilon_{lw} = 12 < \tilde{\varepsilon}_{\ell w}$ and thus the Hopf bifurcation no longer exists.

[9] Note that this lack of endogenous persistence does not actually apply to our model, since white noise sunspot shocks do generate a persistent dynamics of output, as shown in Figures 1.4 and 1.5. Yet, considering these extensions is worwhile since they are known to influence the shape of output dynamics in response to shocks.

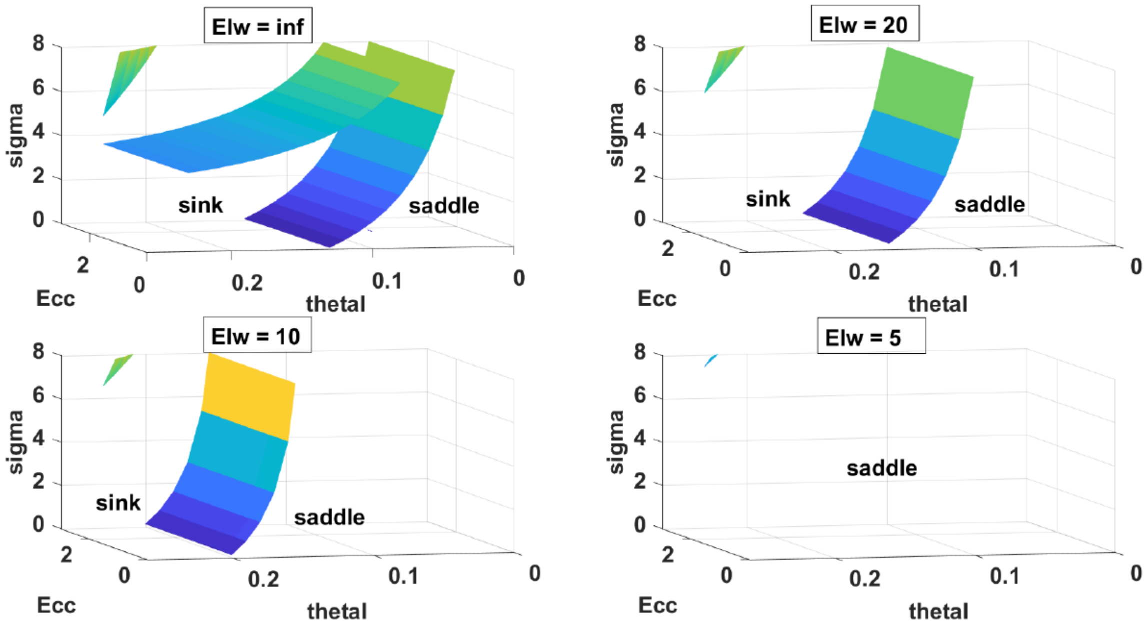


Figure 1.8 – Indeterminacy Area for Different Values of the Aggregate Labor Supply Elasticity.

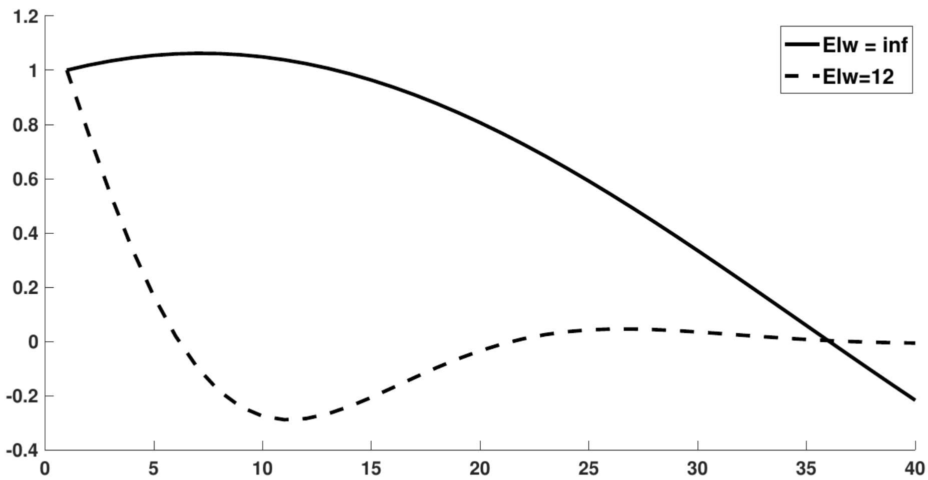


Figure 1.9 – Output Dynamics Following a Positive Sunspot Shock for Different Values of the Aggregate Labor Supply Elasticity.

More precisely, if reducing ε_{lw} does enable to reduce the persistence in the response of output to a sunspot shock, the dynamics is no longer hump-shaped. Moreover, in unreported results, we have experienced with alternative calibrations combining smaller labor supply elasticities with larger degrees of IRS to preserve the indeterminacy property. None of these experiments helped to improve the results.

1.4.3.2 Habits in Consumption

We now introduce habit formation in consumption. There are different ways of doing this, and we chose to adopt a generalized specification of the instantaneous utility function in Boldrin et al. (2001) with internal habits in consumption. We thus consider the following instantaneous utility function:

$$u(c_t, c_{t-1}, l_t) = \frac{(c_t - bc_{t-1})^{1-\rho}}{1-\rho} + Bv\left(\ell - l_t\right)$$

with $b \in (0,1)$ the parameter of habit formation.

Solving the consumer's intertemporal utility maximization problem, we obtain the new first-order conditions characterizing optimal consumption choices:

$$\begin{aligned} Bv'\left(\ell - l_t\right) &= w_t \lambda_t \\ \lambda_t &= \left(c_t - bc_{t-1}\right)^{-\rho} - \beta b E_t \left(c_{t+1} - bc_t\right)^{-\rho} \\ \lambda_t &= \beta E_t R_{t+1} \lambda_t \end{aligned}$$

replacing equations (1.10–1.11) above. All the other equations are the same. Clearly, when $b = 0$ we recover our benchmark model with $\lambda_t = u'(c_t) = c_t^{-\rho}$ and a constant EIS in consumption $\epsilon_{cc} = 1/\rho$. When $b > 0$, the EIS in consumption is also constant but is now given by $\epsilon_{cc} = (1-b)/\rho$. Using a continuity argument, all our theoretical characterizations of the local stability properties of the steady-state hold in a small neighborhood of $b = 0$. In order to consider larger values for b, we rely on numerical simulations. Figure 1.10 displays the flip, Hopf and transcritical bifurcation loci for different values of b ranging between 0 and 0.7. As can be seen, when b is positive but not too large, the model remains in the indeterminacy area for most empirically credible values for ϵ_{cc} , σ, and Θ. When b is increased further, however, the indeterminacy area progressively shrinks, due to a quantitatively significant downward shift in the Hopf bifurcation locus.

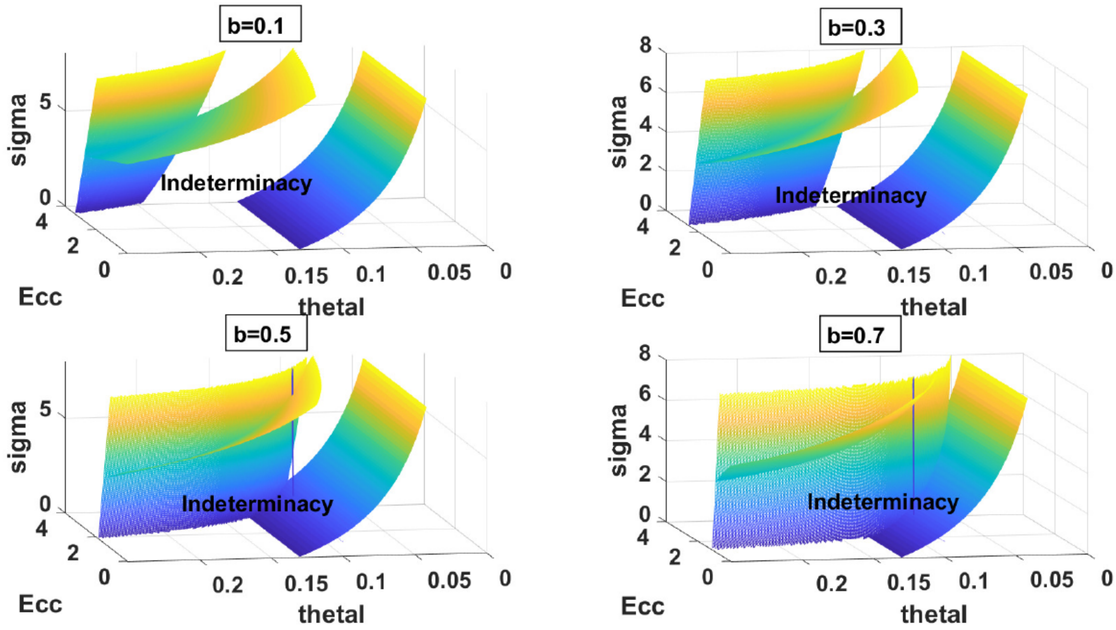
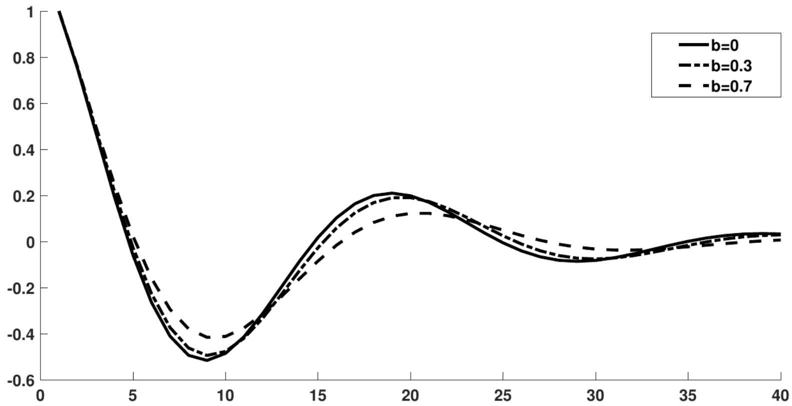


Figure 1.10 – Indeterminacy Area for Different Values of b.

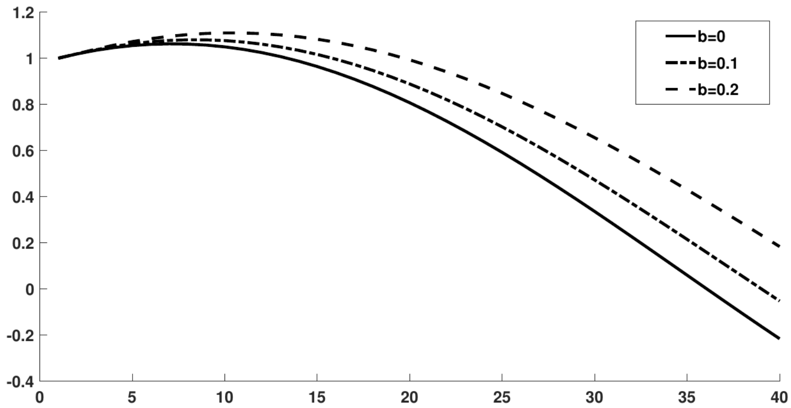
In Figure 1.11, we display the Impulse Response Functions of output to a positive sunspot shock when the value of b is progressively increased, considering two alternative calibrations for the other structural parameters. The initial BW calibration with $\varepsilon_{cc} = \sigma = 1$ and $\Theta = 0.11$ (see Panel A), and our benchmark calibration with $\varepsilon_{cc} = 2.3$, $\sigma = 3$ and $\Theta = 0.16$ (see Panel B). In the first case, we increase b from 0 to 0.7, since the model remains in the indeterminacy area for this whole set of values. In the second case, we increase b from 0 to 0.3, since the model is no longer indeterminate for large values of b under this calibration. As can be seen, in both cases, the effects are quantitatively marginal: an increase in b is associated with a slight increase in the persistence of output following a sunspot shock, but the hump-shaped dynamics is not getting closer to the data.

1.4.3.3 Dynamic Learning by Doing in Production

We now experience with alternative specifications regarding the productive side of the economy, and consider as an example an enriched specification of the production function dis-



Panel A: BW calibration



Panel B: Our benchmark calibration

Figure 1.11 − Output Dynamics Following a Positive Sunspot Shock for Different Values of b.

playing dynamic learning by doing à la Chang et al. (2002). The production function is now:

$$Y_t = Af(u_t K_t, N_t)e(\bar{u}_t \bar{K}_t, \overline{N}_t) \tag{1.21}$$

where $N_t = x_t l_t$ are hours worked by the representative household in efficiency units, $\overline{N}_t$ being the aggregate (economy wide) average, and x_t is the skill level of this household. The latter accumulates as:[10]

$$x_t = x_{t-1}^{1-\phi} l_{t-1}^{\phi} \tag{1.22}$$

with $\phi \in (0, 1]$. When $\phi = 0$, we recover our benchmark case with $x_t = x_{t-1} = x$, i.e. skills are constant over time. The representative firm's profit maximization problem yields the modified optimality condition for hours worked in efficiency units:

$$w_t = Af_2(u_t K_t, N_t)e(\bar{u}_t \bar{K}_t, \overline{N}_t)$$

The representative household maximizes its expected intertemporal utility function subject to the modified budget constraint $k_{t+1} = (1 - u_t^{\gamma}/\gamma)\, k_t + w_t x_t l_t + r_t u_t k_t - c_t$ and the skill accumulation equation (1.22). Denoting by ζ_t the Lagrange multiplier associated to the latter equation, the first-order conditions with respect to l_t and x_t are:

$$\begin{aligned} Bv'(\ell - l_t) &= u'(c_t) w_t x_t + \beta \phi x_t^{1-\phi} l_t^{\phi-1} E_t \zeta_{t+1} \\ \zeta_t &= u'(c_t) w_t l_t + \beta(1-\phi) x_t^{-\phi} l_t^{\phi} E_t \zeta_{t+1} \end{aligned}$$

while other optimality conditions are unchanged.

It turns out that with this specification, the model's dynamic properties are drastically changed as soon as ϕ exceeds 0 by any significant amount. When $\phi > 0$, the model, reduced to its minimal dimension, involves 4 dynamic equations in 4 variables, among which two of them are state variables. As shown in Figure 1.12, when $\phi = 0.01$, the model features a Hopf and a transcritical bifurcation in the 3-dimensional plane defined by ε_{cc}, σ and Θ. However, the Hopf bifurcation is no longer associated with the existence of sunspot equilibria. Indeed,

[10] Chang et al. (2002) consider a non-constant returns-to-scale skill accumulation process. We rather choose a CRS specification to avoid adding too many additional parameters.

when σ crosses the Hopf bifurcation value σ_H, the steady state switches from a saddle path to a source, associated with locally unstable dynamics. Indeed, when $\sigma < \sigma_H$, the model has two stable and two unstable eigenvalues. When σ crosses σ_H, two (initially stable) complex conjugate eigenvalues have a modulus crossing 1, and the steady-state becomes a source associated with four unstable eigenvalues.

The model also features a transcritical bifurcation. Starting from the area for which the steady state is a saddle, if ε_{cc} is increased until it crosses the transcritical bifurcation curve, one real eigenvalue crosses 1 and the steady state becomes a source associated with three unstable eigenvalues. If, on the other hand, ε_{cc} is gradually increased starting from the area where the steady-state is a source associated with four unstable eigenvalues, crossing the transcritical bifurcation locus implies that the model remains a source, but now associated with three unstable eigenvalues. In any case, indeterminacy is ruled out for any empirically credible values for ε_{cc}, σ and Θ.

Finally, Figure 1.12 shows that a similarly negative conclusion is obtained when larger values of ϕ are considered. The main difference is that the Hopf bifurcation curve progressively shifts downward (and eventually totally disappears) when ϕ increases, reducing the area for which the steady-state is a saddle path. Once again, indeterminacy is ruled out. Thus, introducing dynamic learning by doing in the production function does not appear to be a promising road to improve the model's predictions because it tends to eliminate the possibility of existence of sunspot fluctuations.

At this stage, we are led to conclude that although the one-sector model with variable capital utilization rate is able to explain crucial features of the estimated empirical responses of the economy to a standard demand shock, the model is not yet ready to survive a more stringent data confrontation. Other extensions and/or refinements to this model are necessary to improve the model's predictions in this dimension. We leave this discussion for further research.

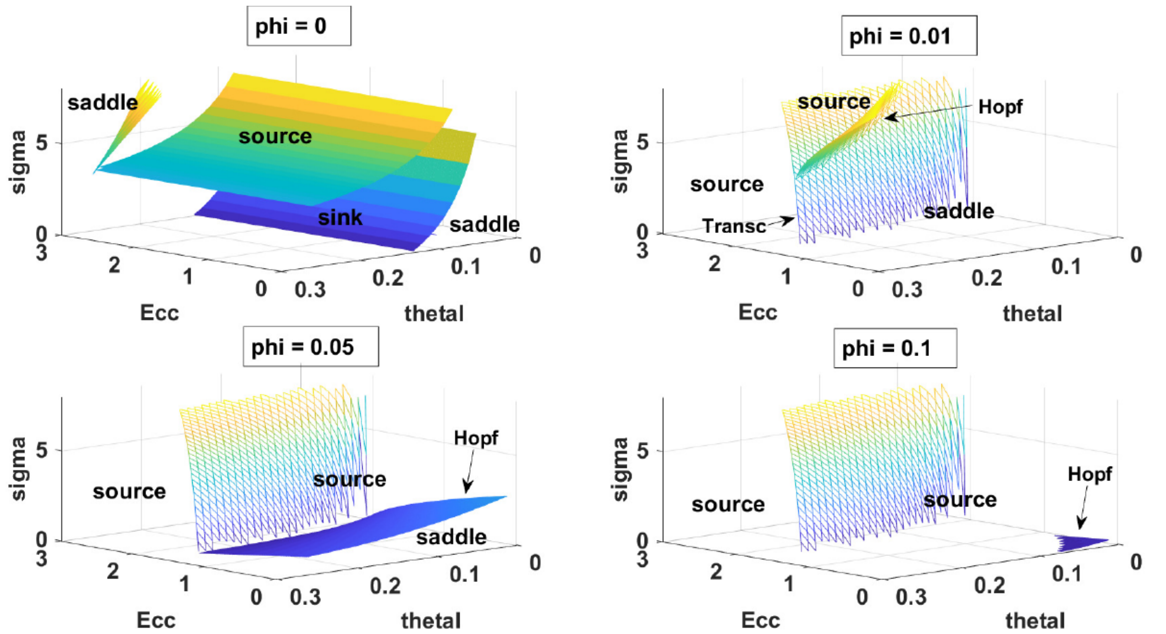


Figure 1.12 – Indeterminacy Area for Different Values of the Returns to Scale Skill Parameter.

1.5 Conclusion

If one wants sunspot fluctuations based on self-fulfilling prophecies to be more credible, a requirement is that endogenous fluctuations models replicate the main stylized facts of a demand shock. Considering a generalized version of the BW model and allowing for more substitution between intertemporal consumption, a moderate increase in factor substitutability and a slightly higher degree of increasing returns, we have shown that, from a theoretical point of view, the one-sector stochastic growth model with variable capacity utilization is able to generate a hump-shaped dynamics of output in response to a pure sunspot shock. Yet, this response is too persistent for the model to be directly confronted to the data. Further research should be done in order to determine which extension of the model should be introduced to improve the results in this dimension. Dufourt, Nishimura, and Venditti (2017) are exploring whether a two-sector stochastic growth model with variable capacity utilization enables the model to come closer to the data.

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2 'Whatever it Takes' to Change Belief: Evidence from Twitter

This chapter is based on a joint research with another PhD candidate, Michael Stiefel (Department of Economics, University of Zurich).

Abstract: *The sovereign debt literature suggests the possibility that a self-fulfilling default crisis might be avoided if markets believe the central bank will act as lender of last resort. This chapter investigates the extent to which changes in belief about an intervention of the European Central Bank (ECB) explain the sudden reduction of government bond spreads for the distressed countries in summer 2012. We study Twitter data and extract belief using machine learning techniques. We find evidence of strong increases in the perceived likelihood of ECB intervention and show that those increases explain subsequent decreases in the bond spreads of the distressed countries.*

2.1 Introduction

In summer 2012, when the eurozone was on the verge of breaking up, the European Central Bank (ECB) gradually announced the Outright Monetary Transactions (OMT) program[1] which gives the central bank the possibility to buy an unlimited amount of short-term govern-

[1] The OMT program was officially announced after the meeting of the ECB Governing Council on September 6th 2012. However, the ECB communication had already changed in the previous two months, so that the literature includes earlier speeches as part of the OMT announcement (Falagiarda and Reitz, 2015, Altavilla, Giannone, and Lenza, 2016, Ambler and Rumler, 2019, Van Der Heijden, Beetsma, and Romp, 2018, Krishnamurthy, Nagel, and Vissing-Jorgensen, 2017).

ment debt in secondary markets under certain conditions. Even though such purchases were never made, sovereign yields of the distressed countries (Greece, Ireland, Italy, Portugal, Spain) fell during this time period.

Pioneered by Calvo (1988), the sovereign debt literature emphasizes the emergence of multiple equilibria when economic fundamentals worsen, namely a fundamental and a self-fulfilling default equilibrium. More precisely, the former equilibrium (i.e. the "good" equilibrium) prices the true level of economic fundamentals whereas the latter equilibrium (i.e. the "bad" equilibrium) generates a self-fulfilling debt crisis triggered by pessimistic investors (Cole and Kehoe, 1996, 2000). Applying this framework to the European sovereign debt crisis, Corsetti and Dedola (2016) and Roch and Uhlig (2018) show that this self-fulfilling default crisis can be avoided if markets anticipate that the central bank will act as the lender of last resort.

In this chapter, we analyze the extent to which changes in belief about an intervention of the ECB explain the sudden reduction of government bond spreads for the distressed countries in the eurozone, as suggested by the literature on self-fulfilling default crises. To study this change, we follow a direct approach by extracting belief from Twitter data. At first, we document that there were large increases in the volume of tweets around important dates of central bank communication, showing that Twitter was used to both communicate and interpret the ECB's actions. Then, we create a belief index of the perceived likelihood of a central bank intervention using techniques from natural language processing. This analysis reveals that the belief index jumps at two important days of ECB communication: the day of ECB president Mario Draghi's 'Whatever it takes' speech and the day of the OMT program announcement. These large increases in our belief index coincide with large decreases in the sovereign spreads of the distressed countries on the same and the following day. We also find that, to a smaller degree, our belief index is sensitive to other events, such as information leaks and rumors. Using a pooled panel estimator, we show further that a one-standard deviation increase in the lagged change in the belief index is associated with a six basis point reduction in the spreads of the crisis countries. To corroborate our findings, we compare changes in beliefs of individual users with several tweets around the dates of ECB communication and also detect strong increases in the belief index at our two identified key dates. We test the performance of our approach against that of traditional event dummy analysis and show that our approach captures more information. Finally, the following robustness checks demonstrate that our results are robust: using spreads of sovereign Credit Default Swaps (CDS), forming alternative versions of our belief index and controlling for the users' level of information using the number of followers similarly to Gholampour and Van Wincoop (2017).

We make three contributions. First, this chapter demonstrates that we can learn from social media data how the public receives news announcements and how, in turn, these announcements influence belief formation and confidence building. Second, we show that capturing this belief formation can improve upon typical event studies. Event studies can be problematic if there is anticipation before or a delayed reaction afterwards that is not inside the event window. By creating an index over the full time horizon, our procedure addresses this issue, is able to capture rumors and information leaks, and can distinguish between the importance of different announcements. Third, even though we do not formally put such a model to the data, our results are consistent with the theoretical prediction that a central bank that credibly commits to an intervention as lender of last resort can eliminate self-fulfilling equilibria. The 'Whatever it takes' episode is widely recognized as a turning point in the sovereign debt crisis in the eurozone, a common narrative in the popular press ("5 years ago, Draghi saved the euro in one sentence" Les Echos 2017) as well as in the economic literature (e.g. Corsetti 2015 in his Schumpeter Lecture). We motivate the channel through which this speech has affected bonds, namely a change in belief leading to the perception of the ECB as a central bank which is willing to intervene to reduce government bond spreads. Over this three-month horizon, our analysis associates a 180 basis points reduction in the 10-year bond spreads of distressed countries due to our identified change in belief.

Related literature

This chapter is related to three branches of the economic literature. First, studies have analyzed whether sovereign risk is priced according to "fundamentals", or whether sentiments and market coordination play a role as well. Second, recent work has investigated the effect of central bank communication on financial markets, and more specifically the announcement of central bank programs on government bond spreads. Finally, a new branch of literature has started to use social media data such as Twitter to analyze financial fluctuations, and also to model the expectation formation about monetary policy.

Several studies have documented that one cannot explain the large increases in government bond spreads leading to the eurozone crisis using fundamental factors alone, such as debt and GDP dynamics; see for instance De Grauwe and Ji 2012, Di Cesare, Grande, Manna, and Taboga 2013. As an explanation, De Grauwe and Ji (2012) highlight miscoordination among market participants, while Di Cesare et al. (2013) point to a perceived break up risk of the eurozone as a potential channel. Bocola and Dovis (2016) provide a quantitative decomposition of the self-fulfilling and fundamental parts of Italy's sovereign risk. Using the model of Cole and Kehoe (2000), they indirectly infer beliefs from observed changes in the maturity structure of government bonds. They find that 12 percent of the Italian spread is explained by rollover risk.

Given the importance of central bank actions in the aftermath of the financial crisis, many studies have investigated the effects of unconventional monetary policy announcements. For the eurozone, event studies have found that just the announcement of central bank policies leads to sizeable effects on government bond yields (see among others Szczerbowicz 2015, Falagiarda and Reitz 2015, Briciu and Lisi 2015, Bulligan and Monache 2018 and Ambler and Rumler 2019). Fendel and Neugebauer (2018) document that the main announcement effects occurs with a delay of one day. The closest paper to ours is that of Altavilla et al. (2016) who study the financial and macroeconomic effects of the OMT program announcements. Focusing on the financial effects in an event study, they show that the OMT announcements triggered a reduction of about 200 basis points in the 2-year government bond yield of Italy and Spain. Furthermore, using a multi-country VAR model and constructing a counterfactual scenario without bond buying program announcements, they show that the announcements had significant effects on Italian and Spanish growth rates.

Our approach differs from the above paper in several dimensions. First, we shed light on the *channel* through which the OMT announcement affected spreads, namely belief. Second, as has been criticized by D'Amico (2016) in the discussion of Altavilla et al. (2016), estimating the financial effect with event dummies does not take into account the expectation formation process in between and after the days of ECB announcements. In this chapter, we address precisely this concern by modeling belief through the entire event period, which allows us to study the possible effects of anticipation, rumors and information leaks.

Another branch of the literature on central bank communication has used tools by computational linguistics to infer different dimensions of central bank communication (Hansen, McMahon, and Prat, 2014, Hansen and McMahon, 2016). Like these papers, we apply machine learning methods to classify text. We focus, however, on extracting information from responses to the central bank communication, not by applying them to the policymakers directly, and by only investigating a unique and pre-specified dimension of the text instead of modeling different topics.

A burgeoning literature studies the impact of Twitter sentiment on financial fluctuations. Pioneered by Bollen, Mao, and Zeng (2011) and Zhang, Fuehres, and Gloor (2011), this literature shows that the general public mood of Twitter users can predict stock market indices.

Gholampour (2017) develops a financial dictionary to proxy the daily sentiment and disagreements of investors to predict financial fluctuations. In the same spirit, Gholampour and Van Wincoop (2017) highlight that Twitter is an important source of information for predicting the euro-dollar exchange rate and show that informed traders share their information on the microblogging social networking platform. Concerning monetary policy, Azar and Lo (2016) perform a sentiment analysis of tweets referring to the Federal Reserve. They show that Twitter sentiment has a large impact on asset prices.

Meinusch and Tillmann (2017) were the first to infer beliefs about monetary policy from Twitter. They investigate the extent to which long-term bond yields and the exchange rate are sensitive to changes in belief about the Federal Reserve's exit from quantitative easing. In order to proxy those beliefs, the authors label and aggregate tweets from April to October 2013, thereby distinguishing the users' opinions on whether the Federal Reserve will taper soon or late. Using a VAR-X model, they identify a belief shock. Their results show that changes in belief have strong and persistent effects on bond yields and exchanges rates. While this chapter is similar in spirit, our extracted belief is not about the timing of a central bank action, but rather about the type of the ECB and its willingness to intervene at all. Moreover, we are interested in the differential effect of this belief on the distressed countries compared to other eurozone countries.

The remainder of the chapter is organized as follows. In section 2.2, we detail the succession of the ECB key events over summer 2012. In section 2.3, we present a simple theoretical model. Our Twitter and financial data are described in section 2.4. In section 2.5, we present our belief index that is used for the empirical analysis in section 2.6. We discuss the results and robustness checks in section 2.7. We look at a different dimension of our Twitter data and compare belief before and after the key dates for individual users in section 2.8. We conclude the chapter in section 2.9.

2.2 Setting

In this section, we first describe the background of our study, the severity of the sovereign debt crisis during summer 2012 and the debate about ECB interventions. Then, we highlight in detail the key ECB actions in this timespan which culminated in the official announcement of the OMT program. Finally, we explain why this background is well suited to our research question.

Our horizon of study, July to September 2012, captures the moment when the sovereign debt crisis in the eurozone was hitting Italy and Spain. This was a critical time for both countries since the financing costs had seen dramatic increases in a short amount of time: the spreads to Germany amounted to less than 100 basis points in 2010, while in summer 2012 they reached close to 600 basis points. In addition, this was also a decisive moment for the eurozone as a whole: the debt crises in Greece, Ireland and Portugal had led to new institutions like the European Stability Mechanism (ESM), but also sparked tensions in other member countries. There was severe resistance to the so-called rescue packages, especially in Germany. A lurking bailout among the larger economies in Spain or Italy would have outsized the already agreed upon emergency funding schemes, and sparked further conflict among the member countries.

The ECB was under increasing pressure to intervene because of the severity of the crisis, but it had remained rather passive until then, mostly focusing on bank liquidity measures.[2][3] Although the Federal Reserve Bank and the Bank of England had already purchased large amounts of government debt as part of their unconventional monetary policy, the ECB had not started a large scale bond buying program as either quantitative easing or as a lender of last resort. Article 123 of the Treaty on the Functioning of the European Union forbids the ECB to directly purchase debt from its member countries. Article 125 of the same treaty - the "no-bailout-clause" - states that no member state is accountable for the debt of other member countries. For this reason, an ECB intervention even in secondary markets for government bonds caused legal concerns.

We now explain the three key communication actions by the ECB that were undertaken in this time horizon and that are today regarded as a fundamental change of ECB policy. Typically, the three actions are jointly regarded as a gradual announcement of the OMT program (Altavilla et al., 2016). However, each event is fundamentally different and might therefore also have affected market expectations in different ways.

On July 26th, talking to financial market participants at the *Global Investor Conference* in London, Mario Draghi made the following remarks:

> "Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough." (ECB, 2012c)

[2] See Szczerbowicz (2015), Falagiarda and Reitz (2015) for detailed accounts of the ECB's actions.

[3] In fact, there were two other ECB programs involving purchases of government bonds on secondary markets, the Securities Market Program (SMP) in 2010, which was replaced by the OMT program, and the expanded Asset Purchase Program (APP) in 2015. Both programs are quite different to the OMT. According to the ECB, both SMP and APP target both public and private securities with the objective of ensuring the monetary policy transmission and price stability. In contrast, the OMT program is specifically designed to reduce yields of distressed countries. Furthermore, the SMP is different because it featured de-facto limits on the purchased amounts of debt and the ECB had seniority on the bonds it purchased (Bruegel, 2012). The APP is a quantitative easing program in which government bonds are purchased but not specifically targeting a specific country, and not allowing for an unlimited amount.

We want to emphasize that Draghi did not choose the official statements around Governing Council meetings for this remark, but an external event with financial market participants. He also directly addresses them and their belief. Neither in this quote nor in the full speech is a direct reference to a new policy program, so the impact of the speech crucially hinges on the market participants' interpretation.

On August 2nd, at the regular meeting of the ECB Governing Council and the subsequent press conference, Draghi went a step further to link his statement to a possible action by the ECB but remained very vague about a specific program. Specifically, Draghi said,

> "The Governing Council (...) may undertake outright open market operations of a size adequate to reach its objective." (ECB, 2012b)

Questioned by a journalist whether his 'whatever it takes' speech was about bond buying by the ECB, Draghi responded:

> "Have you read the speech? Had you read it, you would have seen that there is no reference whatsoever to a bond buying programme." (ECB, 2012b)

As the journalists interrogate him further about whether his remarks were then misinterpreted by markets which seemed to expect the ECB to become active, Draghi then responded:

> "I like these remarks very much. And they were not misinterpreted. Markets simply took their actions based on their expectations following these remarks. That is what happened. And these expectations are what they are." (ECB, 2012b)

Those quotes illustrate again that within the first two main communication events, the ECB did not commit to, but only hinted at, a specific program such that the consequences of Draghi's words effectively depend on the market participants' interpretation. To therefore truly capture those announcement effects, it is necessary to measure the market participants' response to those statements in contrast to event studies which just give a dummy variable for such an announcement day.

Finally, on September 6th, the last main ECB action in this time horizon, the Governing Council officially announced the OMT program. This program gives the ECB possibility to buy an unlimited amount of short-term bonds on secondary sovereign debt markets under certain conditions. Until now, this program has never been activated. Even though the ECB had formally proposed a program, this did not stop discussions about its legality and whether the ECB would actually commit to it. In fact, prominent politicians and lawyers had appealed to the German Constitutional Court, arguing that this program was beyond the ECB's mandate, and those appeals were declared invalid only in 2016. In this regard, the impact of the program still hinged on the expectations of the market participants after the announcement.

We argue that this period around the announcement of the OMT program is an ideal setting to study our research question. While the ECB was very active in *communicating* its intentions, actual purchases within this program were never made. Thus, the change in spreads can be attributed to changes in belief and not to large purchases by the central bank. At that time, Italy and Spain were not part of any rescue package by the ESM or EFSM, i.e. they were fully dependent on private lenders to finance their expenses. Additionally, other confounding factors are minimal within this time horizon. As the work by Altavilla et al. (2016) has shown, controlling for other economic news does not change the effect of the OMT announcements in an event study.

2.3 A Simple Theoretical Model

Let us consider a simple theoretical model in order to describe the economic mechanism induced by the ECB intervention in financial markets during summer 2012. This model is based on Calvo (1988), Lorenzoni and Werning (2013) and Corsetti and Dedola (2016).[4] Consider a small open economy integrated in world capital markets. Time is discrete with period $t = 1, ..., T$.

[4]This model is taken from the international finance course given by Giancarlo Corsetti at the University of Cambridge.

2.3.1 Government

The government faces a financing need FN_t that corresponds to a primary deficit and maturing bonds. A primary deficit is the difference between government spending and revenue from taxes and is negative (if the difference is positive, then it is a primary surplus). In order to meet its financing need, the government issues sovereign bonds B_{t+1} at the market price Q_t.

$$FN_t = Q_t B_{t+1} \tag{2.1}$$

The market price Q_t is set by investors and can differ depending on the expectation of default.

2.3.2 Investors

Domestic and international investors can invest in an international riskless sovereign bond at price $Q^* = \frac{1}{R^{world}}$ and in a sovereign bond issued by the country at the market price $Q_t = \frac{1}{R_t}$. To simplify the computation, let us assume that $R^{world} = 1$ so that $Q^* = 1$. We assume international lenders to be risk neutral such that the price of any asset is equal to the expected cash flow from the asset. The market price Q_t can differ from Q^* because of different investors' perception of risk: the price at which investors are willing to buy bonds depends on how sustainable they believe the debt to be. The price of a risky bond would then be lower than the price of a riskless one due to a higher interest rate.

A debt sustainability issue is more likely to arise when the economy is in a recession and when the country's debt level is above a certain threshold. For these reasons, we make two assumptions. First, we assume that a recession can occur with probability $1 - \psi_H$, where H refers to high output times. Second, we assume that there is a critical level of debt $\hat{B}$ above which the sovereign bonds are at risk of default.

2.3.3 Timing

The timing is as follows:

In period t, the government sells sovereign bonds in order to meet its financing need.

In period t+1, the economy can be in two different states: a high output state (Y_{t+1}^H) with probability ψ_H, and a low output state (Y_{t+1}^L) with probability $1 - \psi_H$. If the country is in the high output state, it can service its debt. If the country is in the low output state, the critical level of debt $\hat{B}$ plays a crucial role. If the level of debt is below the critical threshold, i.e. when $B_{t+1} < \hat{B}$, the government is still able to service its debt. However, if the level of debt is above the critical threshold, i.e. when $B_{t+1} > \hat{B}$, it is too costly for the government to increase taxes and decrease spending, so a default will occur.

Therefore, in each period, the government chooses

$$\begin{cases} \text{no default} & \text{if } Y_{t+1} = Y_{t+1}^H, \\ \text{no default} & \text{if } Y_{t+1} = Y_{t+1}^L \text{ and } B_{t+1} < \hat{B}, \\ \text{default} & \text{if } Y_{t+1} = Y_{t+1}^L \text{ and } B_{t+1} \geq \hat{B}. \end{cases} \tag{2.2}$$

In order to simplify the illustration, we assume that the recovery rate is zero, so that the haircut on sovereign bond holders is 100 percent when default occurs.

2.3.4 Bond Pricing Equilibrium

We now determine the equilibrium price of the sovereign bond. From the previous subsection, it is clear that the risk of default depends crucially on whether B_{t+1} is lower or larger than the fiscal limit $\hat{B}$. If there is no default risk, the sovereign bond is priced at the riskless price Q^*. However, if there is risk of default, investors will charge a higher interest rate that will lower the sovereign bond price Q_t. Hence,

$$Q_t = \begin{cases} Q^* = 1 & \text{if } B_{t+1} < \hat{B}, \\ \psi_H \leq 1 & \text{if } B_{t+1} \geq \hat{B}. \end{cases} \tag{2.3}$$

In Figure (2.1), we plot the fiscal revenue $Q_t B_{t+1}$ against the issuance of sovereign bonds B_{t+1}. We can make two observations. First, we can see that there is a break in the fiscal

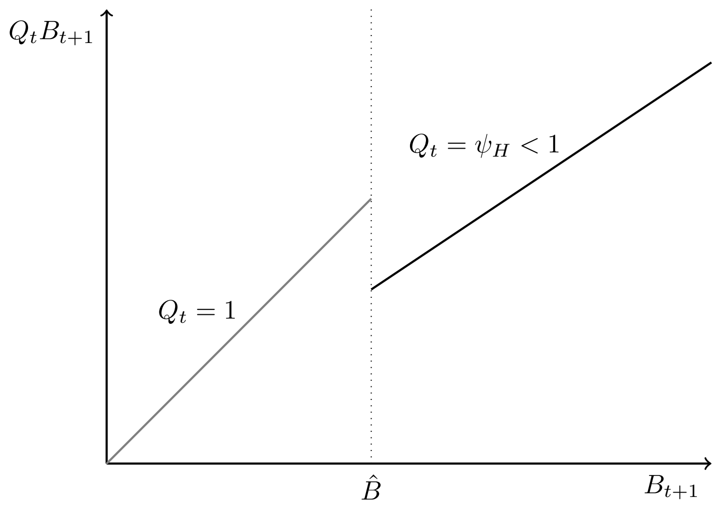

Figure 2.1 – Sovereign Bond Pricing

Note: the figure shows the discontinuity of the revenue function because of the fiscal limit $\hat{B}$. When the sovereign bond issuance B_{t+1} is lower than the fiscal limit $\hat{B}$, the market expects no default and investors buy sovereign bonds at the riskless price $Q_t = 1$ (low interest rate). On the other hand, when the sovereign bond issuance B_{t+1} is larger than the fiscal limit $\hat{B}$, the sovereign bond price is no longer default free and investors buy sovereign bonds at the risky price $Q_t = \psi_H$ (high interest rate).

revenue function at the fiscal limit $\hat{B}$ and that above this limit, the revenue drops critically. Second, the slope of the fiscal revenue is flatter when debt issuance is above the fiscal limit, i.e. more debt needs to be issued in order to reach the same level of revenue.

In addition to the fiscal limit $\hat{B}$, another important element of this model is the level of financial need FN_t. In order to determine the equilibrium price of the sovereign bond, we focus on three different scenarios: i) one with a low level of financing needs, ii) one with a high level of financing needs, and iii) one with intermediate levels of financing needs. Let us first define a range of intermediate levels of financing needs found between a lower bound $\underline{FN}_t$ and an upper bound $\overline{FN}_t$. Figure (2.2) depicts the three different scenarios. First, we can see that for a sufficiently low level of financing need (when $FN_t < \underline{FN}_t$), the model admits a unique equilibrium. This equilibrium is characterized by a riskless sovereign bond price $Q_t = 1$. In this situation, the fiscal conditions are fully sustainable which makes this equilibrum a no default equilibrium. Second, when the government faces a sufficiently large level of financing need (when $FN_t > \overline{FN}_t$), the fiscal conditions are simply too bad and the country defaults. In this situation, the model exhibits a unique equilibrium which is a default equilibrium. Hence, these two situations depict the cases of fundamental equilibria. The third case highlights an interesting scenario in which a self-fulfilling debt crisis is triggered by investors' coordination failures. Such a case appears for intermediate levels of financing needs that are included in $\underline{FN}_t$ and $\overline{FN}_t$, i.e. values of FN_t that are in the crisis zone. Therefore, for a given level of $FN_t \in (\underline{FN}_t, \overline{FN}_t)$, there are two equilibria: a "good" equilibrium with a corresponding riskless price (and a low interest rate), and a "bad" equilibrium characterized by a lower sovereign bond price (and a higher interest rate). The switch between the two equilibria is based on a sunspot variable that captures market psychology. Suppose that the market is optimistic and believes that the country will not default. In this case, investors would require low interest rates and the country could sell its sovereign bonds at the riskless price $Q_t = 1$. The country's bond issuance B_{t+1} would be lower than the fiscal limit $\hat{B}$ and market's initial expectation is "self-validating". Suppose now that investors become pessimistic on the country and coordinate their belief that the country will default. As a result, investors would require a higher interest rate (a risky one) which would increase the pace at which debt would be accumulated. An increase in the debt stock would raise the likelihood that the country becomes insolvent, which would feed the fear of default, and so on and so forth, until the country actually defaults. In this scenario, defaulting would be self-fulfilling and would result from investors' coordination failures.

2.3.5 Ruling Out the Self-Fulfilling Default Equilibrium

We have seen that a self-fulfilling default crisis can appear for a medium range of financing need FN_t. Such a phenomenon arises because of exogenous changes in investors' expectations about the default risk of the country. It is therefore crucial for policymakers to manage investors' expectations in order to rule out the "bad" self-fulfilling default equilibrium. This subsection highlights the way monetary backstops like the OMT program can prevent self-fulfilling default crisis from happening. For this purpose, let us include a central bank in the model. This new agent can also buy a quantity of sovereign bonds B^{CB}_{t+1} from the country at

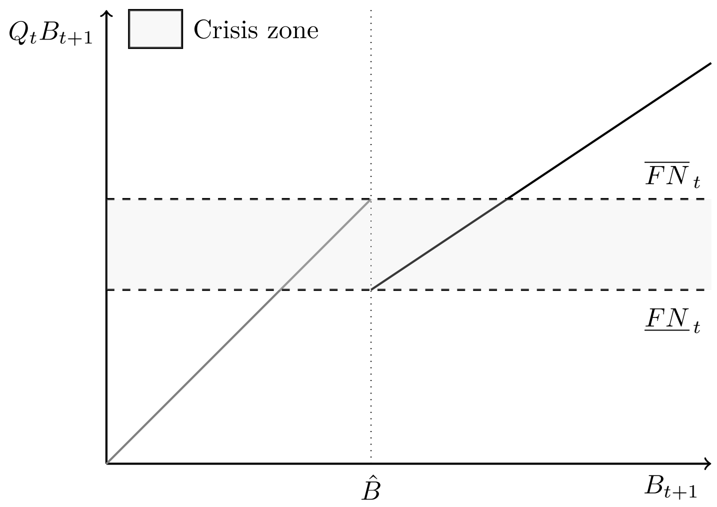

Figure 2.2 – Self-Fulfilling Default Crisis

Note: the figure shows the different sovereign bond price equilibria for corresponding values of the country's financing needs. For a sufficiently low level of financing needs, when $FN_t < \underline{FN}_t$, the model admits a unique (fundamental) equilibrium. For a sufficiently large level of financing needs, when $FN_t > \overline{FN}_t$, the model still admits a unique (fundamental) equilibrium. However, for an intermediate range of financing needs, when $FN_t \in (\underline{FN}_t, \overline{FN}_t)$, the model admits two equilibria. In case of multiple equilibria, a self-fulfilling default crisis can occur if investors coordinate expectations on the "bad" equilibrium.

the market price Q_t^{CB}. Therefore, we have:

$$FN_t = Q_t^{Market} B_{t+1}^{Market} + Q_t^{CB} B_{t+1}^{CB}. \tag{2.4}$$

Suppose that the investors coordinate their beliefs on the "bad" equilibrium. Which central bank intervention could rule out such equilibrium and make investors coordinate expectations on the "good" equilibrium instead? Let us assume that the central bank is willing to buy sovereign bonds at the riskless price. Therefore, $Q_t^{CB} \geq Q_t^{Market}$. By purchasing B_{t+1}^{CB} at the price Q_t^{CB}, the central bank intervention allows the country to sell its sovereign bonds at a higher average price, pushing down interest rates. Let us introduce the following condition:

$$B_{t+1}^{Market} + B_{t+1}^{CB} = \frac{FN_t - Q_t^{CB} B_{t+1}^{CB}}{Q_t^{Market}} + B_{t+1}^{CB} < \hat{B}. \tag{2.5}$$

This condition is key. If it is fulfilled, then a sufficiently large purchase of sovereign bonds by the central bank can always keep the overall debt stock below the fiscal limit $\hat{B}$. To show this, consider the following example. Consider a country with a level of financing needs FN_t that is in the range of equilibrium multiplicity, i.e $FN_t \in (\underline{FN}_t, \overline{FN}_t)$. We can see in panel $a)$ of Figure (2.3) the two equilibria. Let us now turn to panel $b)$ of the same Figure and assume that investors coordinate expectations on the "bad" equilibrium and buy sovereign debt at the risky price. If the central bank buys sovereign bonds at a riskless price $Q_t^{CB} = 1$, then through its intervention, the central bank diminishes the share of sovereign bonds left to the market to finance. As a result, the origin of the revenue curve with the risky price is no longer zero but the point $(B^{CB}, Q_t^{CB} B^{CB})$. We can see that the new revenue curve with the risky price is higher than the one without the intervention of the central bank. Hence, by intervening, the central bank reduces the crisis zone, thereby eliminating the ("bad") self-fulfilling default equilibrium. This would also be the case if markets continued to buy sovereign bonds at a risky price, i.e. B_{t+1} would still be lower than the fiscal threshold $\hat{B}$. However, in this case, the risky price cannot be an equilibrium since the condition that guarantees the existence of this price would be violated.[5] As a consequence, investors price the sovereign bonds by the riskless price.

One might think that the case presented above diverges from the case of the OMT program because such a program has never been activated, meaning that the central bank did not intervene in the sovereign bond markets. In fact, the main point of this model is that debt purchases do not need to happen in equilibrium to prevent a self-fulfilling default crisis. The important variable is that the market believes that the central bank will intervene as lender of last resort when needed. By credibly signalling that it will intervene to an adequate extent on the sovereign bond market, investors understand that the only equilibrium bond price is the riskless one. Hence, no intervention by the central bank will be required ex-post. This chapter is concerned with measuring the credibility of ECB intervention over summer 2012 through the OMT program announcements.

2.4 Data

In this section, we start by justifying the use of Twitter and explaining how our dataset has been constructed. Then, we detail the financial data used in this study.

2.4.1 Twitter

Twitter data presents several interesting features for our analysis. Firstly, Twitter is a large source of opinionated data from individual users. As a microblogging social networking platform, Twitter allowed 200 million monthly users in 2012 to express their opinions on different topics through short public messages. A tweet must be concise (with a limit of 140 characters in 2012) which makes it possible to extract a simple opinion from it. Furthermore, Twitter is a large source of high frequency data. This allows users to quickly react to news and events. In fact, more than 50 percent of tweets in 2012 came from mobile devices.

[5]The condition that guarantees the risky price equilibrium is

$$B_{t+1} = \frac{FN_t}{\psi_H} > \hat{B},$$

$\forall FN_t \in (\underline{FN}_t, \overline{FN}_t)$.

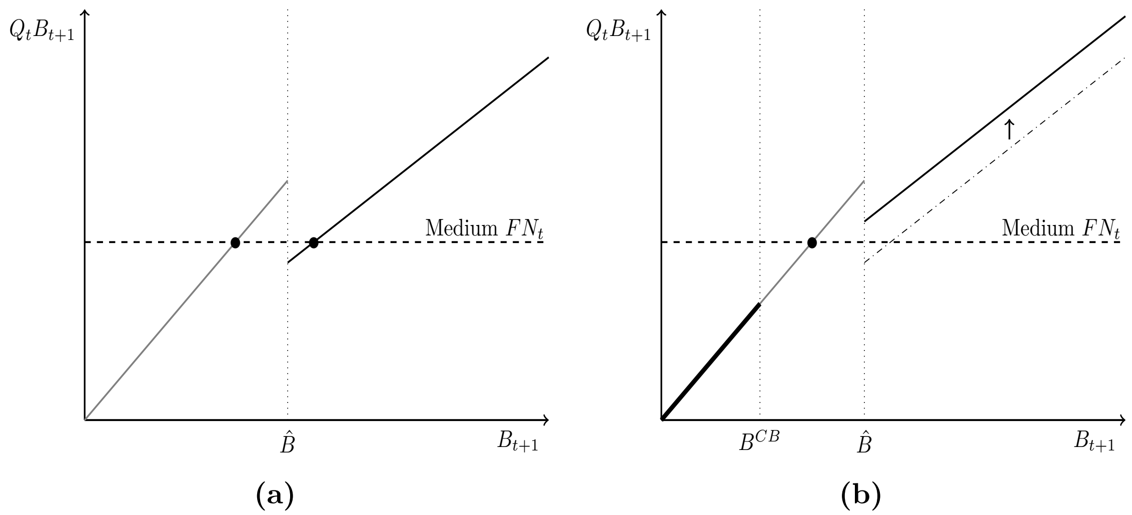

Figure 2.3 – Effect of the OMT Program

Note: the figures show how a monetary backstop from a central bank can rule out a self-fulfilling defaut equilibrium. Suppose a medium level of financing need that generates multiplicity of equilibria, as in panel a). If the central bank buys a sufficient amount of the country's sovereign bond B^{CB}, then it lowers the amount of debt that is left to the market to finance, see panel b). The new revenue curve with a risky price moves upward since it does not originate from (0,0) anymore but from the point ($B^{CB}, Q^{CB}B^{CB}$), thereby eliminating the self-fulfilling default equilibrium.

Finally, a third interesting feature of Twitter data is that users include policymakers, financial journalists, and also traders. Thus, relevant information from all different milieu is shared on this platform.

To construct our dataset, we use web scraping techniques that allow us to extract data directly from the Twitter website based on date and keywords. We collect tweets from July 2nd to October 1st 2012. Each tweet contains at least two of the following keywords: "Draghi", "ECB", "bailout". For each tweet, we gather information about the text content, the number of retweets and favorites, and the user name, user id and tweet id. This method allow us to gather 42,685 unique English tweets from 11,506 accounts after filtering by language and day of the week. We keep only English tweets because English is the main language both in financial markets and on Twitter. Furthermore, we only look at tweets posted on weekdays, since the volume of tweets on weekends is quite low and the daily indices are then fully consistent with the financial data. We add the number of retweets to each tweet in order to control for the number of retweets. For instance, a tweet that has been retweeted 10 times counts for 11 tweets. This mechanically gives a higher weight to tweets which have been retweeted, which can be regarded as a sign of importance. Our dataset is now composed of 49,522 English tweets, as most tweets have not been retweeted.

The daily number of tweets ranges from 13 to 9,601 with a mean of 750 tweets and a large daily variance (see Table B2 for quantiles). Moreover, 90 percent of users have tweeted 8 times or less and 52 percent have only tweeted once. A recurrent question when gathering data based on combinations of keywords is about the relevance of the extracted information. In Figure 2.4, we plot the daily number of tweets. We can observe three main peaks from the series. The first peak, on July 26th, corresponds to the 'Whatever it takes' speech by Mario Draghi. The second peak corresponds to the meeting of the Governing Council of the ECB on August 2nd. Finally, the third peak, on September 6th, relates to the OMT announcement conference. The fact that we can recover the key events of our time horizon from the daily number of tweets shows that Twitter was used to spread and interpret the news from those events. An interesting feature in Figure 2.4 is that we can observe other peaks that are not directly related to the days of ECB communication. Based on the content of the tweets, we can identify that they are also linked to rumors and information leaks. For instance, before the official announcement of the OMT program, Mario Draghi announced that he was cancelling his participation in the Jackson Hole conference at the end of August which led to rumors that the ECB was "up to something big" (see tweet example below). Another example is that on September 3rd, only three days, before the announcement, Mario Draghi spoke to members of the European Parliament in Brussels behind closed doors, but on Twitter and in newspapers there are rumors that Draghi said that buying short-term debt did not breach the EU treaty (El País, 2012).

2.4.2 Financial and Macroeconomic Data

We construct our series of government bond spreads using data from Bloomberg. We retrieve government bond yields for 11 European countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain) for maturities of 2, 5 and 10

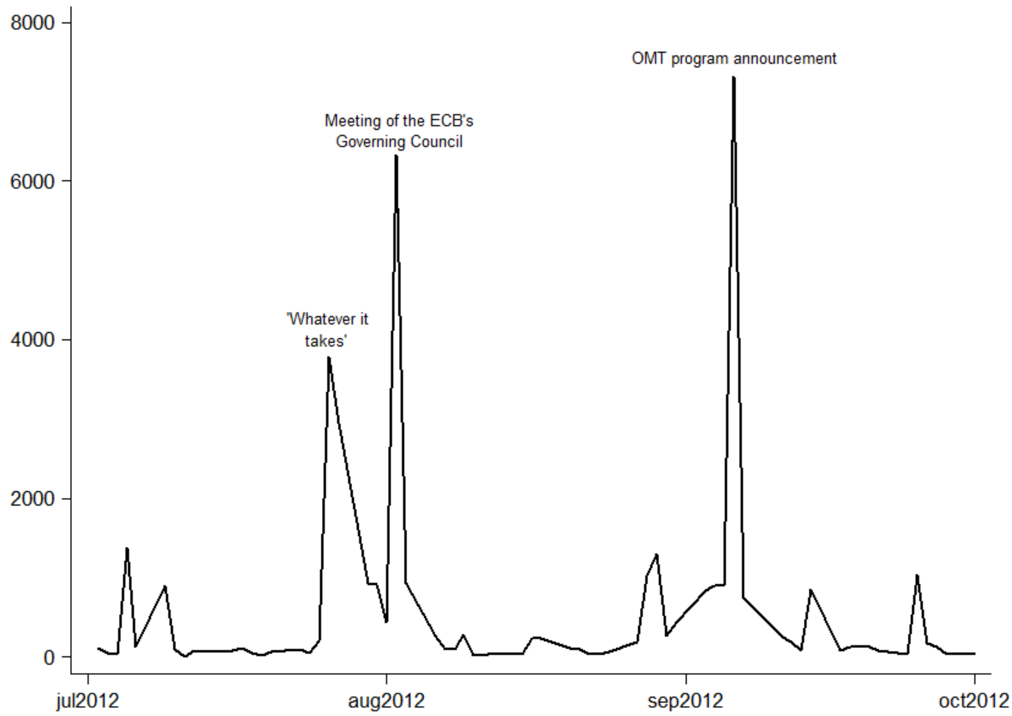

Figure 2.4 – Timeline of the Daily Number of Tweets

Note: the figure shows the number of tweets on the left axis. The three key ECB communication events are the ‘whatever it takes’ speech on July 26th, the day of the meeting of the Governing Council of the ECB on August 2nd, and the day of the OMT program announcement on September 6th.

years over our time horizon of interest, July 2nd until October 1st. Due to data unavailability, we only consider the 10-year maturity spreads for Greece and the 2-year and 5-year maturity spreads for Ireland. For all maturities, the bond spreads are computed relative to Germany.

Furthermore, we consider the European counterpart of the VIX index: the V2TX index. It is an uncertainty index based on the EURO STOXX 50 realtime option prices. We also use the Citi Economic Surprise Index (CESI) for the eurozone. The latter captures macroeconomic surprises by comparing consensus expectations and the state of the economy. This index is often used to control for macroeconomic fundamentals at a daily frequency.

Finally, for robustness checks, we also use the time series on sovereign Credit Default Swaps from Datastream at 2-, 5- and 10-year maturity for the same set of countries except Greece, where the corresponding series are not available.

2.5 A Belief Index on Central Bank Intervention

In this section, we first explain how we construct the belief index. We then show descriptive statistics for this belief index and how it relates to the financial data.

2.5.1 Construction

To extract a measure for the perceived credibility of central bank intervention, we assign a label to each tweet and then compute a daily aggregate. A tweet is assigned the label “1” if an intervention by the ECB is considered to be likely. Similarly, if an intervention by the ECB is not considered to be likely, the tweet is assigned the label “-1”. We give a neutral label, “0”, to those tweets which do not express an opinion about central bank intervention.

To give an example, consider the following tweets:[6]

> *Draghi’s not kidding. My take on his comments and expectations of ECB bond buying*
>
> *ECB ‘willing to buy bonds of weaker EU nations’ says Draghi | It’s a start*

[6] For this exposition, we remove links/hashtags from the tweets to ease readability.

With the cancellation of Draghi trip to Jackson Hole, ECB is up to something big

Draghi reportedly told EU Parliament ECB can buy 3 year bonds and bond purchases are not state financing

The first two examples indicate a clear opinion that the ECB is willing to intervene and receive the label "1". The last two examples are also labeled "1" and show the rumors and information leaks on Twitter.

Now, consider the following examples that express an opinion that the ECB will not intervene and therefore receive the label "-1":

Chatter that other ECB policymakers don't agree with President Draghi's statements yesterday and bond buying is unlikely to be restarted.

Boy, did Draghi blow it today. I was wrong. I thought he and Bernanke were on the same page. Now ECB has lost credibility.

"DRAGHI SAYS ECB MAY UNDERTAKE OUTRIGHT OPEN MARKET OPERATIONS" ... ecb is simply not allowed to do that!

BofA: The ECB will never be able to enforce the centerpiece of its news bailout plan

Further examples including neutral tweets are provided in the appendix in Table B1.

We randomly split the tweets into two different sets. The first set, consisting of 20 percent of the tweets, is labeled manually. Based on this manually labeled dataset, we now employ a double cross-validation procedure to select a machine learning model that can evaluate the remaining unlabeled tweets. This double cross-validation procedure consists of two layers. In the first layer for model assessment, we randomly split this manually labeled set further into a training set (90 percent) and a test set (10 percent). In the second layer for model selection, we train a machine learning classification model to this training set, as explained further below.[7]

The machine learning in our context faces the challenge of learning from textual data. A popular method in this context is the "*n-gram*" approach. At first, preprocessing steps clean the text from links and hashtags.[8] Then, a count vectorizer creates a dictionary in which all words ("tokens") are contained. A tweet can then be regarded as a collection of items in this dictionary. The n-gram method allows to group together n consecutive tokens (in the order in which they appear in the tweet) as an n-tupel so that the final dictionary contains unique words and combinations of those words up to the number n. In many instances, n-tupel allow to catch more meaning. For example, the words in "The ECB will buy government bonds soon" and "The ECB will not buy government bonds soon" are the same with the exception of the single word "not".[9] To measure the importance of an item in this dictionary, we use the tf-idf (term frequency - inverse document frequency) statistic. This statistic assigns a higher value if this item appears more often in the tweet, and a lower value if this item also appears more often in all the other tweets. The final dataset is then a large matrix in which each row is a tweet, and each column corresponds to a dictionary item. The matrix entries correspond to the tf-idf score of each item in the tweet. Since not every word appears in each tweet, this is a sparse matrix, which makes our machine learning approach computationally feasible.

More formally, the problem is to assign one of three categorical targets (the labels "-1", "0", "1") to each tweet based on the explanatory variables which are given here by the tf-idf scores for each dictionary element. For this multiclass classification problem with a large

[7]See Figure B5 in the appendix for an illustration of the procedure.

[8]Stemming or lemmatizing the text do not improve the results. Therefore, we decide to continue our analysis without applying these methods. Stemming is a process that allows to reduce words to their word stems while lemmatization is a process that groups different inflected forms of a word to one single unit.

[9]There is a trade-off between allowing for higher n-grams - that is allowing for more combinations of tokens to capture more meaning - and overfitting since one then allows for many features specific to a single tweet. This trade-off is solved by cross-validating the model on a hold-out set to determine which n-gram model performs best, as explained below.

sparse matrix, a popular classifier is Support Vector Machines (SVM).[10] When this supervised learning model is fit to our manually labeled dataset, it essentially fits a hyperplane to separate the different tweets in a high-dimensional space. This model is then used to predict the labels for the remaining 80 percent of the tweets in the dataset, which have not been manually labeled.

In the model selection part, we need to find the right parameters for the SVM-classifier (also called to "hypertune" the parameters), as well as to determine which n-gram model to choose. We proceed with grid search cross-validation. The training set is again randomly split into 5 different folds, each of which contains 20 percent of the dataset.[11] The classifier is then trained on four folds with different parameters and is tested on the remaining fold. This is repeated five times until each fold has been used for testing once. The classifier then uses the parameters which, on average, perform best in this cross-validation task. This cross-validation procedure was also used to determine that a trigram model, allowing for dictionary items of up to three tokens, performs best. Finally, we now apply the selected classifier on the test set which, of course, has not been used during the training, for model assessment. This allows us to compute an accuracy score for the machine learning which is approximately 93 percent.[12]

2.5.2 Descriptive Statistics

Given the set of labeled tweets, we now proceed to compute daily statistics. 40 percent of tweets consider ECB intervention to be likely, 50 percent are neutral tweets and 10 percent of tweets consider that an intervention of the ECB is unlikely. Since there is a large variance in the daily amount of tweets, we do not consider the mean of labels per day to be a relevant statistic, because it would give a relatively higher weight to tweets on days with a small volume of tweets. Instead, we suggest the following two statistics:

[10] We also tried other kinds of machine learning classifiers such as Logistic Regression, Random Forest, Naive Bayes, k-Nearest Neighbors. However, their performances in terms of predictive accuracy, recall and precision, were worse than what were obtained by the SVM classifier.

[11] See Figure B5.

[12] The classifier also performed well in terms of precision and recall for all three classes.

$$\Delta\text{Belief}_t = \sum_i \text{Tweet}_{i,t}\ \textbf{'1'} - \sum_i \text{Tweet}_{i,t}\ \textbf{'-1'} \tag{2.6}$$

$$\text{Belief}_t = \sum_{j=1}^{t} \Delta\text{Belief}_j \tag{2.7}$$

That is, we compute the daily sum of the labels per day (ignoring the neutral tweets) and interpret this as changes in belief.

As we see in the timeline of the number of tweets in Figure 3.1, users seem to predominantly respond to new events and information. Clearly, when there is no new information and therefore a low volume of tweets, it does not mean that the previous events and changes in belief are no longer important. With this in mind, we obtain the final belief index in levels, Belief_t as the cumulative sum of the previous changes. This interpretation of daily tweets as changes is also implicit in the literature about stock market predictions using Twitter Sentiment. For example, Gholampour (2017) associates stock market changes with Twitter Sentiment which then suggests a relationship between the stock market in levels and the accumulated Twitter sentiment. However, in the robustness section, we also consider different ways of constructing a belief index, such as the mean, and show that our results are qualitatively unaffected. Summary statistics and quantiles are reported in Table A3 in the appendix.

As one can see in Figure 2.5, our belief index has an upward trend with two strong peaks, one at the day of the 'Whatever it takes' speech and another large spike at the day of the official OMT announcement. (For a graph that plots the changes in the belief index, see Figure B1 in Appendix B). Interestingly, in spite of a large volume of tweets on August 2nd when the Governing Council of the ECB met, we do not find an aggregate change in belief on this day. As we outlined in the setting, the ECB communication on August 2nd was ambiguous. On the one hand, the ECB did not announce any new specific program which

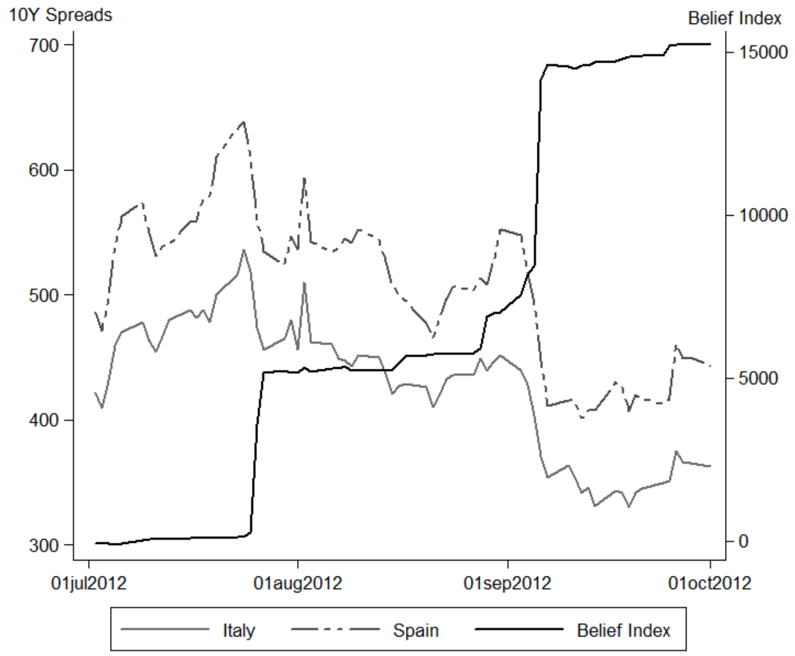

Figure 2.5 – Bond Spreads and Belief index

Note: this figure shows the government bonds spreads of Spain and Italy in basis points relative to Germany (left hand side) and the belief index created from Twitter (right hand side).

might look like a step back after the 'Whatever it takes' speech in the previous week. On the other hand, Mario Draghi signaled that the ECB might engage in a bond buying program without outlining formal details. From the Twitter data, we can clearly observe two types of reactions. First, there were tweets expressing disappointment which mirrors the behavior of the 10-year maturity spreads in Figure 2.5. Second, there were tweets welcoming Draghi's statement about outright open market operations and therefore regarding ECB intervention as still likely to occur. The latter reaction slightly dominates in the aggregate in our analysis. We note that this behavior of our belief index is different from typical event studies, which regard August 2nd as one part of the OMT-announcement, see for instance Altavilla et al. (2016).

Finally, we also observe that our belief index is sensitive to rumors and information leaks. For instance, the change in belief on August 16th is associated with tweets about a statement by German Chancellor Angela Merkel supporting the ECB's approach for reducing borrowing costs of indebted countries. As shown in the example tweets, Draghi's cancellation of the Jackson Hole meeting and his appearance in front of the European Parliament in Brussels led to speculations that the ECB was preparing a program. Unlike an event study analysis, our approach allows us to capture the effects of those events.

We also run a principal component analysis in order to see by how much our belief index is correlated with the first principal component of the spreads. The results show that the correlation between our belief index and the first principal component is 0.91, and this first principal component explains 70 percent of the variation in spreads. Hence, even though we just look at one dimension which might explain the variation in government bond spreads and other factors like uncertainty and macroeconomic surprises might play a role as well, our belief index seems to capture the relevant parts of the actual movement in the data.

In the next section, we dig deeper into how changes in the belief index are related to changes of the government bond spreads, and how it might have differently affected crisis and non-crisis countries.

2.6 Empirical Strategy

We want to understand whether changes in our belief index can explain the changes in the government bond spreads of the distressed countries. We estimate the following pooled panel regression:

$$\Delta \mathrm{s}_{it} = \alpha_0 + \beta_1 \Delta \mathrm{Belief}_{t-1} + \beta_2 \Delta \mathrm{Belief}_{t-1} \mathrm{xCrises}_i + \mathrm{X}_t + \mathrm{D}_t + u_{it}, \tag{2.8}$$

in which $\Delta \mathrm{s}_{it}$ is the change in the spread of country i on day t, computed relative to Germany. $\Delta \mathrm{Belief}_t$ is the standardized change in our belief index. We further interact $\Delta \mathrm{Belief}_t$ with Crisis_i, an indicator variable for the countries that faced a sovereign debt crisis (Greece, Italy, Ireland, Portugal and Spain). This interaction term is our coefficient of interest and shows the differential effect of changes in belief on the crisis countries relative to the non-crisis countries (Austria, Belgium, Finland, France and the Netherlands). To account for possible endogeneity, we mainly focus on the lag of the changes in belief, $\Delta \mathrm{Belief}_{t-1}$. Looking at the effect of the belief index in lags is not unusual. Most event studies allow for a two-day window and Fendel and Neugebauer (2018) document that the announcement effects of ECB unconventional policies seem to occur with a lag in general. The authors also demonstrate that there is no anticipation effect on the sovereign bond market around unconventional monetary policy announcements in the euro area, which suggests that focusing on the lag of the changes in the belief index is enough to account for possible endogeneity in our case.

X_t is a set of control variables. We control for other common factors that could equally explain changes in government bond spreads. We are using the European uncertainty index $\mathrm{V2TX}_t$ based on the EURO STOXX 50. Furthermore, to control for changes to macroeconomic fundamentals at a daily frequency, we are using the CESI macroeconomic surprise index CESI_t. Ideally, we would like to control with a surprise index for each country in our dataset, but unfortunately, such a news index does not exist for every country.

Finally, D_t is an event dummy variables that controls for the three ECB announcement dates: July 26th, August 2nd and September 6th. We use two specifications based on the event dummy: a one-day event window and a two-day event window, which allows effects to also occur on the subsequent day. The choice of using a one-day and a two-day event window is in line with the recent literature on monetary policy announcements (see among others Haitsma, Unalmis, and de Haan 2016 and Georgiadis and Gräb 2016 for one-day windows or Altavilla et al. 2016, Szczerbowicz 2015 and Christensen and Krogstrup 2018 for two-days windows). All variables are standardized to simplify the interpretation.

2.7 Results and Robustness

2.7.1 Results

Table 2.1 – Regression Results for 10-Year Government Bond Spreads

	(1)	(2)	(3)	(4)
ΔBelief$_t$	-0.812			-0.910
	(1.002)			(1.006)
ΔBelief$_t$ x Crisis$_i$	-6.741^{***}			-5.668^{***}
	(1.470)			(1.487)
ΔBelief$_{t-1}$		-0.195		-0.203
		(1.014)		(1.006)
ΔBelief$_{t-1}$ x Crisis$_i$		-6.028^{***}	-6.028^{***}	-4.747^{***}
		(1.489)	(1.008)	(1.487)
Time Fixed Effects	No	No	Yes	No
Clustered Standard Errors	No	No	Crisis + Time	No
Observations	585	585	585	585
R^2	0.073	0.050	0.303	0.104

*p<0.1; **p<0.05; ***p<0.01

Note: the dependent variable is the government bond spread with 10-year maturity for all euro area members with available data. $\Delta Belief_t$ is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Greece, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France and the Netherlands.

In Table 2.1, we present the results from estimating equation (2.8) using data for 10-year maturity bonds without adding any other regressors. We expect a positive change in the belief index to be associated with a reduction in the spreads of the crisis countries. In column (1), we focus on the effect of changes in belief on the same day. We see that a one-standard deviation change in the belief index has a sizable and significant negative effect of -6.7 basis points on the 10-year bond spreads of the crisis countries. We also run this regression with a lagged change in belief index in columns (2). The coefficient stays significant with only a slightly smaller magnitude of approximately -6 basis points. From this finding, we conclude that the result is not driven by reverse causality of changes in spreads feeding into our belief index. We also see that the coefficient of the change in the belief index on the non-crisis countries is negligible and not significant. This result is in line with the literature that shows that the sovereign bonds of the periphery countries are more sensitive to ECB's unconventional monetary policy announcements, see for instance Bulligan and Monache (2018) and Fendel and Neugebauer (2018). In column (3), we remove this regressor in order to add time fixed effects without having a multicollinearity problem. We cluster the standard errors by the crisis countries and time.[13] The magnitude and the significance of the results remain unchanged. In Table B4 in the appendix, we show that the results also go through for bonds of maturities of 5 or 2 years. However, the latter are not directly comparable due to data unavailability for single countries, Greece is only contained in the table for 10-year maturity, and Ireland only for 2 and 5-year maturity bonds. In column (4) we include both the contemporaneous and lagged change in belief, a similar specification to a two-day event window in an event study. Both coefficients on the interaction terms indicate an economically meaningful effect on the bond spreads of the crisis countries. On average, a standard deviation change in the belief index reduces their bond spreads by 5.7 basis points on the same day and by 4.7 basis points on the following day.

We now add further control variables. We focus on the lag in the change in belief index which is conservative since this effect is smaller than the contemporaneous effect and it

[13]We believe that those are the dimensions among which standard errors might be correlated. It turns out that clustering rather reduces the standard errors. The results are robust, however, to not including them or including them individually.

rules out reverse causality concerns. Results are shown in Table 2.2. In column (1) and (2), we add changes in the European uncertainty index V2TX and we also control for changes in macroeconomic surprises using changes in the CESI index. Those factors enter with a positive sign but their respective coefficients are not significant. However, our coefficient of interest is still highly significant and remains of the same size. Those results show that the change in the sovereign bond spreads of the European crisis countries were not driven by a change in uncertainty or macroeconomic fundamentals. In further regressions not reported here, we find that the result also holds when using the Scotti macroeconomic surprise index for the eurozone (Scotti, 2016), or when further interacting the common uncertainty and macroeconomic surprise factors with the crisis countries.

It could be that these results are mainly driven by the three ECB announcements of our time horizon. In column (3) and (4), we estimate equation (2.8) adding an event dummy variable to control for the ECB announcements dates: July 26th, August 2nd and September 6th. We include one-day and two-day event dummies in column (3) and (4) respectively. These variables enter with expected large and significant negative signs. The effect of a change in the belief index on the crisis countries when using a one-day dummy variable is unchanged, but the latter is reduced by half when one increases the window of the dummy variable up to two days. However, the inclusion of these variables still leaves the coefficient at a sizable magnitude of a 3.2 basis point reduction, and is still significant at a one percent level. The result that the coefficient of a change in the belief index on the crisis countries remains significant shows that our approach captures more information than a simple dummy approach analysis around the three ECB announcement dates of summer 2012. This fact indicates that there is further relevant information in our belief index likely due to rumors, information leaks or by better accounting for varying impacts of different announcement dates.

Another way to test whether our approach captures more information than a simple dummy approach analysis is to estimate a model in the spirit of Altavilla et al. (2016), and compare the explanatory power of the model with and without our belief index. In Table (2.3), we estimate equation (2.8) controlling for changes in macroeconomic surprises,

Table 2.2 – Regression Results for 10-Year Government Bond Spreads With Controls and Event Dummies

	(1)	(2)	(3)	(4)
$\Delta\text{Belief}_{t-1}$	0.139	-0.272	-0.270	0.331
	(0.751)	(0.430)	(0.452)	(0.753)
$\Delta\text{Belief}_{t-1}$ x Crisis_i	-6.028^{***}	-6.028^{***}	-5.935^{***}	-3.244^{***}
	(0.254)	(0.172)	(0.184)	(0.312)
ΔV2TX_t	5.073			
	(3.817)			
ΔCESI_t		1.383		
		(1.774)		
EventDummy_t			-1.408	
			(4.419)	
EventDummy_t x Crisis_i			-12.404^{***}	
			(1.848)	
TwoDay – EventDummy_t				-4.093
				(3.875)
TwoDay – EventDummy_t x Crisis_i				-16.869^{***}
				(1.625)
Time Fixed Effects	No	No	No	No
Clustered Standard Errors	Crisis + Time	Crisis + Time	Crisis + Time	Crisis + Time
Observations	585	585	585	585
R^2	0.120	0.052	0.060	0.084

*p<0.1; **p<0.05; ***p<0.01

Note: the dependent variable is the government bond spread with 10-year maturity for all euro area members with available data. $\Delta Belief_t$ is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Greece, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France and the Netherlands. ΔV2TX_t *is the standardized change in the EURO STOXX 50 Volatility Index and* ΔCESI_t *is the standardized change in the Citigroup Economic Surprise Index.* EventDummy_t *is an indicator variable with the value 1 on July 26th, August 2nd and September 6th.* TwoDay – EventDummy_t *is also an indicator variable which additionally includes the following day.*

ΔCESI_t, and for the three ECB announcement dates of summer 2012. For each model, we compute the Root Mean Square Error (RMSE) and the Akaike Information Criterium (AIC), first with our belief index included, and then with the belief index removed. We observe that the results presented in this table are in line with the ones obtained so far. In column (1) and (2), we include a one-day event dummy. The RMSE and AIC criteria are minimized when we include our belief index in the specification. One can note the very strong difference between the AIC criteria between the two columns: the AIC of column (1) is 26.667 lower than the one of column (2). In column (3) and (4), we repeat this procedure, increasing the span of the event dummy up to two days. The RMSE and AIC criteria are again minimized for the specification in which we include our belief index, thereby confirming that our approach improves the explanatory power of the model.

Overall, our index $\mathrm{Belief_t}$ increased to approximately 15,000 at the end our three-month horizon. With a standard deviation of 830, we have roughly 18 standard deviation increases in this time. Multiplying this with the interaction coefficient for the crisis countries on the same and the following day (columns (4) in Table 2.1), this back-of-the-envelope calculation implies that, on average, the 10-year government bond spread of crisis countries was reduced by 180 basis points due to this change in belief. This effect is mainly driven by the 'Whatever it takes' speech (a 4 standard deviation increase on the same day and a 2 standard deviation on the following day, accounting for an 63 basis points reduction on average) and on the day of the official OMT-announcement (a 7 standard deviation increase on the same day and 0.5 on the following day, accounting for a 78 basis points reduction on average). This result is in line with the finding by Altavilla et al. (2016) who report a 200 basis points reduction in the bond yields of Spain and Italy due to the OMT announcements.

2.7.2 Robustness

We propose three robustness checks. At first, we focus on an alternative measure of sovereign risk, namely spreads of Credit Default Swaps (CDS). Then, we propose alternative versions of our belief index. Finally, we refine our analysis controlling for the number of followers.

Table 2.3 – Regression Results for 10-Year Government Bond Spreads With and Without the Belief Index

	(1)	(2)	(3)	(4)
$\Delta\text{Belief}_{t-1}$	-0.355		0.274	
	(0.428)		(0.767)	
$\Delta\text{Belief}_{t-1}$ x Crisis_i	-5.935^{***}		-3.244^{***}	
	(0.175)		(0.318)	
ΔCESI_t	1.502	1.080	1.634	1.561
	(1.833)	(1.548)	(1.863)	(1.780)
EventDummy_t	-1.634	$-$ 0.774		4.279
	(4.542)	(4.660)		(3.202)
EventDummy_t x Crisis_i	-12.404^{***}	-13.445^{***}		
	(1.899)	(1.899)		
$\text{TwoDay} - \text{EventDummy}_t$			-4.321	-3.641
			(4.005)	(2.792)
$\text{TwoDay} - \text{EventDummy}_t$ x Crisis_i			-3.244^{***}	-23.125^{***}
			(0.318)	(1.163)
Time Fixed Effects	No	No	No	No
Clustered Standard Errors	Crisis + Time	Crisis + Time	Crisis + Time	Crisis + Time
Observations	585	585	585	585
R^2	0.063	0.012	0.087	0.079
RMSE	18.410	18.899	18.167	18.247
AIC	5082.239	5108.906	5066.713	5067.821

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: the dependent variable is the government bond spread with 10-year maturity for all euro area members with available data. $\Delta Belief_t$ *is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Greece, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France and the Netherlands.* ΔCESI_t *is the standardized change in the Citigroup Economic Surprise Index.* EventDummy_t *is an indicator variable with the value 1 on July 26th, August 2nd and September 6th.* $\text{TwoDay} - \text{EventDummy}_t$ *is also an indicator variable which additionally includes the following day. RMSE and AIC stand for Root Mean Square Error and Akaike Information Criterion, respectively.*

2.7.2.1 Credit Default Swaps

Credit Default Swaps are a financial derivative which allows lenders to insure against the risk of a default by the debtor. The buyer of the CDS has to pay a fee ("spread") for this insurance, typically quoted in basis points. Naturally, this spread is higher when a default is considered to be more likely. Hence it will be similar to sovereign bond spreads. For our purpose CDS spreads are a good comparison for robustness, since we lack bond spreads for Ireland at 2-year and 5-year maturity but do have the CDS spread.

Table 2.4 shows the results for the CDS spreads with maturity of 10 years. A one-standard deviation increase in the change in the belief index reduces the spreads of crises countries by between 3.6 and 4 basis points on the same day and by between 1.6 and 2.5 basis points on the following day, depending on the specification. The results are significant throughout at the 5 percent level. Interestingly, in the regressions with CDS, the stand-alone term ΔBelief_t is also significant but of a smaller magnitude of less than one basis point and only at the 10 percent level. Table B5 in the appendix shows similar results for CDS spreads referring to 2 and 5-year maturities.

2.7.2.2 Alternative Belief Indices

We now propose two robustness checks regarding the construction of the belief index. At first, we propose a new *definition* of the index. Second, we propose two alternative *measures* of the belief index.

Up to this point, we were considering both beliefs "1" and "-1". We now turn to an alternative version of our belief index in which we only take into consideration the number of belief "1".

$$\Delta\text{Belief}_t^{alt} = \sum_i \text{Tweet}_{i,t} \textbf{ '1'}$$

This alternative index is motivated theoretically if one assumes that the economy is in the self-fulfilling default equilibrium to begin with and can either stay or switch to the fun-

Table 2.4 – Regression Results for 10-Year Credit Default Swaps

	(1)	(2)	(3)	(4)
ΔBelief_t	-0.755^{*}			-0.793^{*}
	(0.437)			(0.443)
ΔBelief_t x Crisis_i	-3.980^{***}			-3.608^{***}
	(0.675)			(0.689)
$\Delta\text{Belief}_{t-1}$		-0.058		-0.018
		(0.456)		(0.443)
$\Delta\text{Belief}_{t-1}$ x Crisis_i		-2.459^{***}	-2.459^{***}	-1.644^{**}
		(0.705)	(0.913)	(0.689)
Time Fixed Effects	No	No	Yes	No
Clustered Standard Errors	No	No	Crisis + Time	No
Observations	650	650	650	650
R^2	0.112	0.031	0.402	0.125

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: the dependent variable is the CDS spread with 10-year maturity for all euro area members with available data. $\Delta Belief_t$ *is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Ireland, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France, Germany and the Netherlands.*

damental "good" equilibrium. In other words, we consider the expression of a belief "1" as a change in belief itself. $\Delta\text{Belief}_t^{alt}$ is plotted in Figure B2 in Appendix B.

Table 2.5 reports the results using the alternative belief index that only takes into account tweets that are labelled "1". A one-standard deviation change in the lagged alternative belief index has a significant negative effect of -6.9 basis points on the 10-year bond spreads of the crises countries. This result is in line with the initial belief index.

We propose two alternative measures of the belief index. The methodology we have used up to now takes into consideration the volume of tweets. By doing so, a larger weight is given to the days with a higher volume of tweets. An alternative approach is to use the daily mean Mean_t, which is the mean of all labels on day t.

$$\text{Mean}_t = \frac{\Delta \text{Belief}_t}{\sum_i \text{Tweet}_{i,t}} \tag{2.9}$$

Another alternative measure takes into consideration agreement about a positive change in belief. We measure this agreement by computing $\mathrm{PositiveRatio_t}$, which is the number of tweets with label "1" divided by the number of tweets with labels "0" and "-1".

$$\text{Pos.Ratio}_t = \frac{\sum_i \text{Tweet}_{i,t}\ \textbf{'1'}}{\sum_\mathrm{i} \text{Tweet}_\mathrm{i,t}\ \textbf{'0'} + \sum_i \text{Tweet}_i\ \textbf{'-1'}} \tag{2.10}$$

Hence, a larger value of $\mathrm{PositiveRatio_t}$ is associated with more agreements toward a positive change in belief. The changes in these indices are plotted in Figures B3 and B4 in Appendix B. Results are given in column (2) and (3). We can observe that the corresponding coefficients have a slightly lower magnitude compared to the previous measure, but they are still of economically meaningful size and highly significant.

2.7.2.3 Controlling for the Number of Followers

Up to now, we have considered all the tweets to be equal. This is possibly problematic since users might differ in their level of information, in their importance as an information provider or as a market participant. In general, when working with such mainly anonymous data, this is an unsolved question. Also, even if we had complete information on the users, it is conceptually not clear how to weight, for example, a journalist who possibly influences many market participants, the market participants themselves, or the actual decision-makers. One possible attempt in the literature has been to control for the level of information by using the number of followers (Gholampour and Van Wincoop, 2017). This sets a threshold at 500 followers. Then, when a user's number of followers is lower (larger) than 500, the user is considered to be uninformed (informed). We go a step beyond this by adding an additional restriction: we focus on the users that are active on the topic and have tweeted

Table 2.5 – Regression Results for 10-Year Government Bond Spreads With Alternative Indices

	(1)	(2)	(3)
$\Delta\text{Belief}^{alt}_{t-1}$	-0.583		
	(0.995)		
$\Delta\text{Belief}^{alt}_{t-1}$ x Crisis_i	-6.883^{***}		
	(1.445)		
Mean_{t-1}		0.046	
		(0.972)	
Mean_{t-1} x Crisis_i		-5.464^{***}	
		(1.328)	
$\text{PositiveRatio}_{t-1}$			-0.462
			(0.962)
$\text{PositiveRatio}_{t-1}$ x Crisis_i			-5.174^{***}
			(1.293)
Time Fixed Effects	No	No	No
Clustered Standard Errors	No	No	No
Observations	585	585	585
R^2	0.073	0.043	0.047

*p<0.1; **p<0.05; ***p<0.01

Note: the dependent variable is the government bond spread with 10-year maturity for all euro area members with available data. $\Delta Belief_t$ *is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Greece, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France and the Netherlands. See equations (2.9) and (2.10) for the definitions of* Mean_t *and* PositiveRatio_t.

more than once. Results of estimating (2.8) taking into account only users with more than one tweet and more than 500 followers is shown in Table 2.6. Again, results hold with the same order of magnitude and are highly significant. Interestingly, Gholampour and Van Wincoop (2017) find different results when controlling for the users' level of information. Our result is therefore consistent with a general change in belief during summer 2012, whatever the level of information of the users.

Table 2.6 – Regression Results for 10-Year Government Bond Spreads, Belief Index Only Computed Based on Accounts With More Than 500 Followers

	(1)	(2)	(3)	(4)
ΔBelief_t	-0.833			-0.935
	(1.000)			(1.003)
ΔBelief_t x Crisis_i	-6.798^{***}			-5.667^{***}
	(1.466)			(1.481)
$\Delta\text{Belief}_{t-1}$		-0.245		-0.257
		(1.011)		(1.003)
$\Delta\text{Belief}_{t-1}$ x Crisis_i		-6.230^{***}	-6.230^{***}	-4.932^{***}
		(1.483)	(1.065)	(1.481)
Time Fixed Effects	No	No	Yes	No
Clustered Standard Errors	No	No	Crisis + Time	No
Observations	585	585	585	585
R^2	0.075	0.054	0.305	0.108

*p<0.1; **p<0.05; ***p<0.01

Note: the dependent variable is the government bond spread with 10-year maturity for all euro area members with available data. $\Delta Belief_t$ is the standardized change in the belief index, computed after all tweets from accounts with less than 500 followers have been deleted. We use daily data from July 2nd to October 1st. Crisis countries are Greece, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France and the Netherlands.

2.8 Changes in Belief for Individual Users

In this final section, we look at a different dimension of our Twitter data and compare belief before and after the key dates for single users. First, we sort the tweets for each user and compute the mean of labeled tweets before and after the key central bank events, like the 'Whatever it takes' speech. Second, we compute a t-test for paired samples to detect whether the difference in means is indeed pointing in a certain direction.

Since most of the users in our sample just tweet once and we require labeled tweets before and after key events, the number of users here is reduced. However, the sample still consists of more than 1,400 users with tweets before and after the 'Whatever it takes' speech and more than 3,300 users for the ECB Governing Council meetings on August 2nd and

Table 2.7 – Paired t-tests

Date	N	Diff	SD	H1	p
26.07.2012	1462	0.255	0.532	> 0	< 0.001
02.08.2012	3470	-0.071	0.644	< 0	< 0.001
06.09.2012	3330	0.212	0.627	> 0	< 0.001

Note: this table shows results for paired sample t-tests at the three key dates of ECB communication. We compute the mean of labelled tweets after and before the key date and then take the difference. We then test whether the mean difference across all users is statistically greater than zero (for July 26th and September 6th) or smaller than zero (for August 2nd).

September 6th. We compute the mean of labeled tweets for each user, since the number of tweets varies and only this allows comparison across users.

Table 2.7 reports the results of our paired t-tests. For all the users with tweets before and after a key date, we compute the mean of labeled tweets after and before and then the difference. We then compute the average and the standard deviation across all users, which is reported in the third and fourth column of Table 2.7. Interestingly, the mean difference is positive for July 26th and September 6th, meaning that users perceived an ECB intervention to be more likely after those events. For August 2nd, however, the mean difference is negative, meaning that users perceived an ECB intervention to be less likely after this event. We can formally test whether those mean differences are indeed significantly greater than zero for July 26th and September 6th using a one-directional t-test for paired samples. The p-values are smaller than any common significance level, thus we conclude that there are indeed within-user changes in belief at those key dates.

These results are consistent with the earlier, aggregate evidence that belief mainly changed at two events, the day of the 'Whatever it takes' speech and the day of the OMT-announcement. The ambiguous meeting of August 2nd, on the other hand, caused a small negative change in belief about central bank intervention of individual users.

2.9 Conclusion

This chapter pursues a new approach to studying the financial effects of the OMT program announcements. We apply a textual analysis to Twitter data in order to extract belief about the perceived likelihood of a central bank intervention. We show that a belief index based on tweets spikes at two important dates of ECB communication: the day of the 'Whatever it takes' speech and the day of the official announcement of the OMT program. Empirically, our belief index can account for sizeable decreases of the bond spreads of distressed countries in the eurozone. We contribute to the literature in three ways: First, in line with other recent work (Meinusch and Tillmann, 2017), we show that social media data reveals useful information concerning expectation formation about monetary policy. This contribution might also be relevant in different fields because survey data at high frequency is typically unavailable. Second, we show that this methodology can improve on simple event studies because it can account for the formation of expectation over the full horizon and not only on event days. Comparing our belief index to the work by Altavilla et al. (2016), our results look similar to a dummy approach at two points in time - the day of the 'Whatever it takes' speech and the day of the official announcement of the OMT program. However, our results are markedly different for the ambiguous communication after the Governing Council meeting on 2nd August, where we do not find evidence of aggregate changes in belief, and on an individual user level, even evidence for a negative change in belief. Furthermore, our belief index captures rumors and information leaks in advance of event days. Given those findings, we regard our belief index as a "microfoundation" of event dummies. Third, although we do not formally test a sovereign debt model, our results indicate that a credible commitment by a central bank to act as lender of last resort can be used as a coordination device in a sovereign debt crisis.

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3 Twitter Political Climate and the Pricing of Sovereign Debt: the Case of Italy

This chapter is based on a joint research project with another PhD candidate, Laura Sénécal (Aix-Marseille Univ., CNRS, EHESS, Centrale Marseille, AMSE).

Abstract: *In this chapter, we investigate the link between political climate and the pricing of sovereign debt. In order to proxy political climate, we extract public sentiment from tweets mentioning the Italian government from January 2010 to December 2017 using a dictionary-based approach. We find that positive change in Italy's political climate predicts decreases in the Italian 10-year sovereign bond spread, thereby showing that political climate provides additional predictive power beyond the traditional determinants of sovereign bond spreads.*

3.1 Introduction

The traditional view put forward in the literature on sovereign risk holds that fundamental factors, such as sovereign credit risk, sovereign liquidity risk, and global risk aversion, are key to determining the levels of sovereign bond spreads (see among others, Manganelli and Wolswijk 2009, Arghyrou and Kontonikas 2012 and Afonso, Arghyrou, and Kontonikas 2015). Liu (2014) builds on this view by adding an additional determinant, providing evidence that textual sentiment from news, together with the volume of news, could play a role in the price-setting of sovereign bonds. In this chapter, and in line with Liu (2014), we investigate the link between textual sentiment and the pricing of sovereign debt. Specifically, we examine the relationship between Italy's political climate, defined as the aggregate mood and opinions about the Italian government, and the pricing of long-run Italian sovereign debt.

We concentrate on Italy because of a consensus among scholars in a number of fields that Italy's social, political, and economic organization is especially unstable. There are a number of factors which contribute to this instability. Italy's political system is characterized by historical party instability (Marangoni and Verzichelli, 2015, De Giorgi, 2018) and systemic corruption (Vannucci, 2009). The way in which Italy's political institutions are organized, as well as the manner in which Italian political actors conduct their affairs, similarly feed this instability (Fabbrini, 2012, Mancini, 2013). Additionally, problems with the structural sustainability of Italy's debt and deficit (Balassone, Francese, and Pace, 2013), together with its weak economic performance (Pelloni and Savioli, 2015), have fueled tensions between political actors. Despite a scholarly awareness of these aspects of Italian society, no study has yet investigated in depth the role of Italy's political climate on the pricing of its sovereign debt.

In order to proxy the Italian political climate, we collect Twitter data mentioning the Italian government from January 2010 to December 2017. First, we observe large increases in the volume of tweets around major political events. This increase shows that Twitter was used to diffuse and comment on the political news of Italy. We then create a monthly political climate index that measures the positive/negative tonality of the tweets by using a straightforward dictionary-based approach. Specifically, we draw on the Harvard IV general positive/negative word list. Equipped with this Twitter Political Climate Index (TPCI), we estimate the effect of changes in Italy's political climate on the changes in the Italian 10-year sovereign bond spread using an Autoregressive Distributed Lag (ARDL) model. In this analysis, we also control for the traditional determinants of sovereign bond spreads.

Our results suggest that improvements in Italy's political climate predict short-run negative changes in the long-run Italian sovereign bond spreads. More precisely, a one-standard deviation increase in our political climate index is associated with a 5.19 basis point reduction in the 10-year Italian sovereign bond spreads. We also show that including the TPCI variable significantly improves the model's predictive power.

Our results are robust to two kinds of robustness checks. For one, we construct an alternative political climate index that also controls for the volume of tweets. For the other, we filter informed versus non-informed accounts using information about each account's number of followers. Finally, we also extend our analysis by investigating the effect of other indices, such as the Italian Economic Policy Uncertainty (EPU) index, the Business Confidence Indicator (BCI) or the Business Confidence Climate (BCC) index, on the Italian sovereign bond spread and by comparing the performance of those indices with our own.

This chapter makes three contributions. We show that Twitter was used to diffuse and comment on information that relates to the Italian government, therefore demonstrating that Twitter is a rich source of data about Italian politics. We also demonstrate that political climate can predict long-run sovereign spread. In so doing, we show that political climate provides predictive power in addition to the traditional determinants of sovereign bond spreads. Finally, ours is the first study that uses Twitter data to investigate the pricing of sovereign bonds over such a long time horizon.

The chapter is structured as follows. In section 3.2, we describe Italy's political instability during the period under study. Section 3.3 aims at presenting the Twitter data and showing how we construct our political climate index. We present the macroeconomic and financial variables in section 3.4. Section 3.5 includes the empirical analysis. Section 3.6 concludes.

Related literature

This chapter draws on three different literatures dedicated to investigating particular factors that contribute to variations in European sovereign bonds spreads. First, we take up the literature on traditional sovereign bond spread determinants. Second, we engage the literature that finds textual sentiment to be an additional driver of sovereign bond spreads. Third, we participate in a literature that investigates the link between political factors and financial markets.

A large body of literature has investigated the determinants of long-run sovereign bond spreads. These studies suggest that the evolution of bond pricing relies on three main risk factors, namely sovereign credit risk, sovereign liquidity risk and global risk aversion, as mentionned in Manganelli and Wolswijk (2009), Arghyrou and Kontonikas (2012) and Afonso et al. (2015). The first driver is sovereign credit risk, which captures sovereign solvability. Sovereign credit risk usually relies on three factors: a country's fiscal conditions, its macroeconomic performance, and its external competitiveness. Studies highlight that the deterioration of the economic conditions of a country leads to a higher risk of default which significantly raises sovereign bond spreads, see among others Attinasi, Checherita-Westphal, and Nickel (2009). The second driver of sovereign bond spreads is sovereign liquidity risk, which refers to the ease with which a bond can be resold. Higher liquidity risk generates a flight-to-liquidity and increases the risk premium asked by investors, resulting in higher pricing of sovereign debt (see for instance Longstaff 2004 and Schwarz 2018). The third commonly cited driver of sovereign bond spreads is the global risk aversion factor, which captures the level of perceived international financial risk. Several studies emphasize the significant impact of global risk aversion on sovereign bond spreads' evolution (see among other Codogno, Favero, and Missale 2003 and Haugh, Ollivaud, and Turner 2009). During periods of crisis, there is a flight-to-quality from risky bonds to safer ones, which results in a higher sovereign bond spreads for riskier countries.

The literature understands the impact of each traditional determinant to vary according to both the country and the period under study, see for instance Ferrucci (2003) and Alexopoulou, Bunda, and Ferrando (2010). The majority of studies that evaluate the traditional determinants of European Monetary Union (EMU) sovereign bond spreads exploit panel data and end their analyses at the end of sovereign debt crisis (Aristei and Martelli 2014 and Özmen and Yaşar 2016). In this chapter we focus on the Italian case so as to consider the country's economic specificities, and our period of study covers the sovereign debt crisis period as well as the post-crisis period.

This chapter belongs to a second strand of literature which considers textual sentiment to be a fully-fledged driver of sovereign bond spreads (Beetsma, Giuliodori, De Jong, and Widijanto, 2013, Caporale, Spagnolo, and Spagnolo, 2018, Erlwein-Sayer, 2018). The closest papers to ours are Zoli (2013) and Liu (2014). Zoli (2013) analyses news related to the sovereign debt crisis and to international and Italian political and economic events. Zoli categorizes news as either "good" or "bad" and finds a strong correlation between the tonality of this news and the Italian 10-year sovereign bond spread between 2008 and 2012. Liu (2014) studies the effect of sentiment in news on the evolution of the sovereign bond spreads of the GIIPS countries (Greece, Ireland, Italy, Portugal and Spain) between 2009 and 2012. The author finds that higher media pessimism together with the higher volume of news result in higher sovereign bond spreads.

We differ from both analyses in several points. First, we conduct our sentiment analysis on Twitter data while Zoli (2013) and Liu (2014) focus on more traditional sources, including newspapers and press releases. Second, instead of extracting sentiment from economic and financial news, we focus on the political climate related to the Italian government. Third, we consider both the sovereign debt crisis and the post-crisis periods, such that our period of study is longer than that of both of these analyses. Finally, we show that textual sentiment alone can predict the evolution of the Italian sovereign bond spread, while Liu (2014) only finds a significant effect when the sentiment and volume of news are considered together.

We conduct our textual analysis on data extracted from Twitter. Unlike newspapers, which mainly aim at disseminating information, Twitter is used not only to share information, but also to share opinions and serve as a platform for discussions and debates. In the past decade, textual analysis has been applied to Twitter data to capture public opinion and predict financial market fluctuations (Mittal and Goel, 2012, Bollen, Mao, and Zeng, 2011, Chen and Lazer, 2013, Si, Mukherjee, Liu, Li, Li, and Deng, 2013, Oliveira, Cortez, and Areal, 2017). Sentiment derived from Twitter has also been used to measure public political opinion, and has been shown to be a good predictor of election results (O'Connor, Balasubramanyan, Routledge, and Smith, 2010, Tumasjan, Sprenger, Sandner, and Welpe, 2010, Burnap, Gibson, Sloan, Southern, and Williams, 2016, Barberá and Rivero, 2015). Twitter has been used specifically to capture political opinion in Italy: for instance, Ceron and Curini (2014) analyze the popularity of Italian politicians in 2011. They find high correlation between tweets and traditional polling methods on political opinion and show that Twitter sentiment can predict Italy's election results. We aim to bridge these two approaches: on the one hand, we take political opinion on Twitter as the object of our analysis, and on the other hand, we harness Twitter data's predictive power for the financial markets. Some scholars have begun to combine these approaches. The closest paper to ours is Nisar and Yeung (2018) who find that Twitter political sentiment affected the FTSE stock market around the 2016 UK local elections. In our study, we explore the effect of Twitter political climate on Italian sovereign bond spread movements without focusing on a specific event.

Last but not least, this chapter is connected to the literature that examines the political determinants of the sovereign bond spreads. For instance, Eichler (2014) study 27 emerging countries from 1996 to 2009 and finds significant correlation between high sovereign bond spreads and parliamentary systems, low quality of governance and political instability, with stronger effects for autocratic regimes than democratic ones. There is ample evidence that financial markets are sensitive to political cycles. Block and Vaaler (2004), for example, suggests that in the period before elections, sovereign credit ratings change more frequently, and sovereign bond spreads are higher. Their result shows that both investors and rating agencies are sensitive to election periods. The literature has also assessed the impact of political communication on the European sovereign bond spreads (Gade, Salines, Glöckler, and Strodthoff, 2013, Mohl and Sondermann, 2013). For example, Conrad and Zumbach (2016) studies statements made by European political figures to show that their communications impact European bond markets. Significantly for our study, they show that political statements about Italy impact the markets the most. In view of the critical increase in uncertainty in recent years, a large body of literature has investigated the role of political uncertainty in the financial markets (Cuadra and Sapriza, 2008, Leippold and Matthys, 2017, Fang, Yu, and Li, 2017). Political uncertainty refers to situations of unknown information about a government's future policies, its political system, or electoral outcomes. The paper most related to our study is that of Handler and Jankowitsch (2018), who analyze the Italian sovereign bond market during the sovereign debt crisis. They investigate to what extent political uncertainty, proxied by the economic policy uncertainty (EPU) index, and political events, such as the Euro, G8 and G20 summits, affect Italian sovereign bond pricing. Their results reveal that uncertainty about those events causes both a drop in bond prices and a surge in bond illiquidity before those events which last until uncertainty is resolved. This literature suggests that global political uncertainty makes bond investors more risk averse, which impacts sovereign bond pricing and sovereign risk. A large body of literature evaluates the effect of political risk on the sovereign bond market with the same general objective of considering political determinants of sovereign bond spreads (Moser, Moser, Baldacci, Gupta, and Mati, 2011, Duyvesteyn, Martens, and Verwijmeren, 2016). Political risk refers mainly to the risk that political changes may affect economic conditions. For instance, Huang, Wu, Yu, and Zhang (2015) find that the effect of international political crises on sovereign bond yields depends on the stability of the political system at hand. They highlight that political risk creates uncertainty about future policies, which in turn affects sovereign bond returns.

Current research on political determinants of sovereign bond spreads examines political events and news, political risk and political uncertainty. To the best of our knowledge, the relationship between a country's political climate (aggregate political opinion) and its bond pricing has not yet been explored. In this vein, Dergiades, Milas, and Panagiotidis (2014), like our study, analyzes public reaction to political events in Italy (in this case, Silvio Berlusconi's scandals) in relation to variation in the Italian sovereign bond spread. Unlike our study, which focuses on public opinion (sentiment), Dergiades et al. (2014) focuses on the level of public interest (volume) in a single politician. Their study shows what they call "Berlusconi talk" accounts for up to ten percent of the Italian sovereign bond spread's variation between May 2009 and May 2013. By investigating political opinion related to the Italian government and over a longer time span, we aim to show that political climate provides additional predictive power beyond the traditional determinants of sovereign bond spreads. In the next section we highlight how the case of Italy provides strong grounds for our investigation by describing the instability of the Italian political system.

3.2 Italian Political Instability from 2010 to 2017

We begin this section with a brief explanation of our time horizon and a general discussion of the organization of Italy's parliament. We then proceed chronologically by cabinet, detailing important moments in Italian politics that have contributed to its instability. This section then concludes with two short paragraphs on general factors that have contributed to Italy's political instability during the period under study.

Our time horizon includes the latter half of the Sixteenth Legislature (2008-2013) as well as the majority of the Seventeenth Legislature (2013-2018). Numerous political events and government changes took place during this period, which make it a particularly rich one for our study. Indeed, although this period saw only two legislatures (and therefore a single parliamentary election), there were five different governments, each of which was headed by a different President of the Council (equivalent to a prime minister): Berlusconi IV (2008-2011), Monti (2011-2013), Letta (2013-2014), Renzi (2014-2016) and Gentiloni (2017-2018). This period saw a number of changes in government personnel because of shifting alliances between each President of the Council and members of parliament. Briefly, the Italian parliament is divided into two chambers: the Chamber of Deputies and the Senate. The parliament is perfectly bicameral, meaning that both chambers share the same functions during the legislative process. Each President of the Council is not elected during a parliamentary election, but is instead appointed by the President of the Republic from the majority coalition. In order to remain President of the Council, this individual must keep the confidence of both chambers of parliament, which is tested by periodic confidence votes. Unsurprisingly, this system gives rise to a need for the President of the Council to form coalitions with other parties in both chambers so that he might maintain the majority vote during the confidence votes. This system of coalitions has played a strong role in the making and breaking of Italian governments (De Giorgi, 2018).

Berlusconi IV (2008-2011)

Our dataset begins in January 2010. During this same year, there were a number of political events that triggered the fall of of the Berlusconi IV Cabinet. The fall of his cabinet was provoked by four political, economic, and judiciary factors (Chiaramonte and D'Alimonte, 2012, Fella and Ruzza, 2013, Benvenuti, 2017). First, at this time, Silvio Berlusconi withstood a number of scandals about his personal life and business activities. These scandals culminated in the sentencing of Berlusconi's Fininvest company for corruption on July 9, 2011, during which Berlusconi was named "co-responsible". Second, the President of the Council had to manage an internal crisis in his own political party, which concluded with Gianfranco Fini, the co-founder of the governing party, asking for Berlusconi's resignation. Third, the European sovereign debt crisis struck Europe in 2011. Berlusconi could not reassure the markets and the international community regarding the management of the crisis. And fourth, as a result of the combination of these factors, he lost his parliamentary majority. Berlusconi resigned on November 12, 2011. The President of the Republic, Giorgio Napolitano, charged Mario Monti to form a government.

Monti (2011-2013)

The Monti Cabinet was a technocratic solution to the management of the sovereign debt crisis, whose formation was highly influenced by the international community (Marangoni and Verzichelli, 2015). The particularity of this cabinet is that it was not legitimately elected and was composed of experts. Monti introduced the concept of 'national obligation' in order to implement 'mandatory' structural reforms to guarantee the sustainability of public finance, and to implement policies to promote sustainable growth. Due to the critical need for the reforms, and despite their unpopularity, Monti was supported by a cross-partisan coalition that allowed him to keep the confidence of both chambers of the Parliament (Fabbrini, 2013a). After Berlusconi's conviction for tax fraud in October 2012, the former President of the Council decided to return to the forefront of Italian politics and changed his strategy: he and the members of his party abstained from two confidence votes in the Senate and the Chamber of Deputies. Losing a part of his parliamentary base as a result, Mario Monti resigned in December 2012, which marked the end of the Sixteenth Legislature.

Letta (2013-2014)

The 2013 legislative and presidential elections generated a political fiasco (D'Alimonte, 2013, De Sio, Emanuele, Nicola, and Aldo, 2013). After the legislative elections, Italy found itself at a political impasse, with a left-wing majority (Democratic Party) at the Chamber of

Deputies and a Senate with no majority. In addition, the major winner of this election was the populist Five Star Movement, which obtained the third largest number of votes (Passarelli and Tuorto, 2014). This situation paralyzed Italy's political institutions. No one was successful in forming a majority coalition, nor could anyone agree on a new candidate for President of the Republic, which forced the outgoing president Giorgio Napolitano to run for another presidential term. Napolitano's reelection in April 2013 marked the first time that an outgoing President of the Italian Republic was elected for a second term.[1] Also during this period, the leader of the Democratic Party, Pier Luigi Bersani, resigned. In this unstable political context, the only way to form a government was to resort to a grand coalition between the left-wing and the right-wing parties. The technocrat Enrico Letta became President of the 62nd Cabinet of the Italian Republic on April 2013. His cabinet experienced significant instability because of this uncomfortable coalition between two parties that up till this point were traditionally adversaries (Ceron and Curini, 2014). The new leader of the Democratic Party, Matteo Renzi, ousted Enrico Letta, who resigned on February 14, 2014. Renzi was appointed President of the Council on February 17 and won the parliamentary confidence vote in February 25.

Renzi (2014-2016)

The political instability during the Renzi Cabinet stemmed from Renzi's introduction of two controversial reforms. In October 2014, Renzi introduced a labor reform, the "Job Act", to make the Italian labor market flexi-secure (Picot and Tassinari, 2015). He also put forth a constitutional reform whose objective was to put an end to parliament's perfect bicameralism with the goal of stabilizing the Italian political system and improving the legislative process (Pasquino and Valbruzzi, 2017). This reform had two parts. First, Renzi proposed a bill that would create a new voting law, called "Italicum", concerning the composition of the Chamber of Deputies. This law would favor stable majorities by guaranteeing 50 percent of the seats in the Chamber of Deputies to the party that wins at least 40 percent of the votes. The rest of the seats would be given proportionally. Italicum was passed in May 2015. Second, he

[1]Giorgio Napolitano would resign in January 2015 and was be replaced by Sergio Mattarella.

proposed a referendum on the reform of the Italian constitution aimed at changing the composition and role of the Senate. This reform was highly controversial and faced significant opposition from many parliamentarians. Renzi had announced that he would resign if the majority voted "no" on the referendum. Because of this announcement, Italians treated the referendum as a vote on Renzi himself, as though a "no" vote were a way of ousting Renzi (Ceccarini and Bordignon, 2017). Nearly 60 percent of Italians voted "no" on the reform, and as a result, Renzi resigned in December 2016. The President of the Republic, Sergio Matteralla, asked the Minister of Foreign Affairs Paolo Gentiloni to form a government.

Gentiloni (2017-2018)

Because Italicum passed and the reform proposed by the referendum did not, the Chamber of Deputies and the Senate now had two different types of elections. The success of only half Renzi's constitutional reform left Italy's parliamentary system in even greater disarray than before. The Gentiloni Cabinet's primary task was to remedy this pressing issue by quickly preparing and voting on a new electoral law before the 2018 legislative elections. This task was made difficult by Forza Italia's and the Five Star Movement's refusal to support and participate in the government, which lead to a narrow governmental majority. An agreement was reached in extremis in December 2017. The Parliament was dissolved on December 28, 2017, in anticipation of the 2018 legislative elections.

Silvio Berlusconi

Silvio Berlusconi has always played an ambiguous role in Italian politics. His political career was defined by a series of crusades waged against various adversaries, including other politicians and the entire judicial institution. His personal scandals motivated him to attempt multiple times to change the law so as to protect himself from imprisonment and other repercussions. Berlusconi was thus a highly unpredictable element who embroiled Italy's institutions in his own personal troubles. His actions also highlight Italy's problem with systemic corruption (Vannucci, 2009).

Personalization and dramatization

The way in which politicians traditionally conduct their political affairs in Italy affects the country's political climate. Italian politics is marked by a significant degree of personalization, such that the personality of the individual politician takes the greatest share of the public perception of a party or a party's policies (Caprara, Schwartz, Vecchione, and Barbaranelli, 2008, Campus, 2010, Fabbrini, 2013b). Italian politics also features a high degree of dramatization (Mancini, 2013). Politicians infuse their stories with charged emotions and polarizing oppositions that increase the distance between political actors, contributing to political instability. As Mancini writes of Beppe Grillo, founder of the Five Star Movement, "it is not by chance that Grillo comes from the world of theater and television and that his predominant skills are that of drama and spectacle. His language is extreme–his mission is to fight the many "corrupted" who sit in Parliament" (Mancini, 2013).

3.3 Twitter Data and Twitter Political Climate Index

We start this section by describing our Twitter data. We then detail the construction of our political climate index.

3.3.1 Twitter Data

Twitter is a good source of information for our analysis for several reasons. First, Twitter is a platform for sharing news, but it is also an interactive platform where users discuss and debate news, which makes it a good source of data for studying political climate. Second, Twitter users react to current events quickly and as they happen, which makes it a source of high frequency data. Third, Twitter includes the opinions of journalists and politicians, but it also includes the opinions of a broad spectrum of users from the general population. Finally, messages on Twitter ("tweets") are limited to a small number of characters each. This restriction requires users to condense and simplify their opinions, making information easily identifiable.

To gather data about Italy's political climate, we use web scraping techniques to extract information directly from Twitter website. Our period of study covers 8 years, from January 1st 2010 to December 31th 2017. In order to select only relevant tweets, we filter our data with keywords. We extract only tweets that contain both of the keywords "Italian" and "government". For each tweet, we extract the tweet content, the number of retweets and likes, the date of the tweet, and information about each corresponding user, including the number of followers. In total, we gather 138,690 English tweets from 62,398 different accounts. We collected 2,506 tweets on average per month, with a minimum of 192 and a maximum of 15,350.

We focus on tweets in English rather than Italian for several reasons. First, English is the most spoken language on the financial markets and on Twitter (34 percent in 2013 according to MIT Technology Review 2013) while Italian is ranked 13th (less than one percent according to the same source). Second, we understand Italian political topics to be of international importance because what happens to Italy matters outside of Italy. Its economy is the third largest in the Eurozone, and its political affairs affect the entire European Union. Thus political events in Italy make international news and provoke international discussions.

One might ask to what degree data gathered with keywords is relevant to our topic of study. In Figure 3.1, we plot the monthly number of tweets mentioning the Italian government. We can identify the four Italian general elections held during this period in our graph: the election of Mario Monti in November 2011, Enrico Letta in April 2013, Matteo Renzi in February 2014, and Paolo Gentiloni in December 2016. The match between the peaks in our graph and the dates of elections confirms that Twitter was used to share and comment on Italian political news. We can also identify other minor peaks. Based on the content of these tweets, we can see that they relate to political scandals and other important political events. For instance, the third largest peak starts by the end of August and lasts three months. During this period, Berlusconi asked five ministers from his political party to quit the coalition government of Enrico Letta and called for new elections after being convicted for tax fraud.

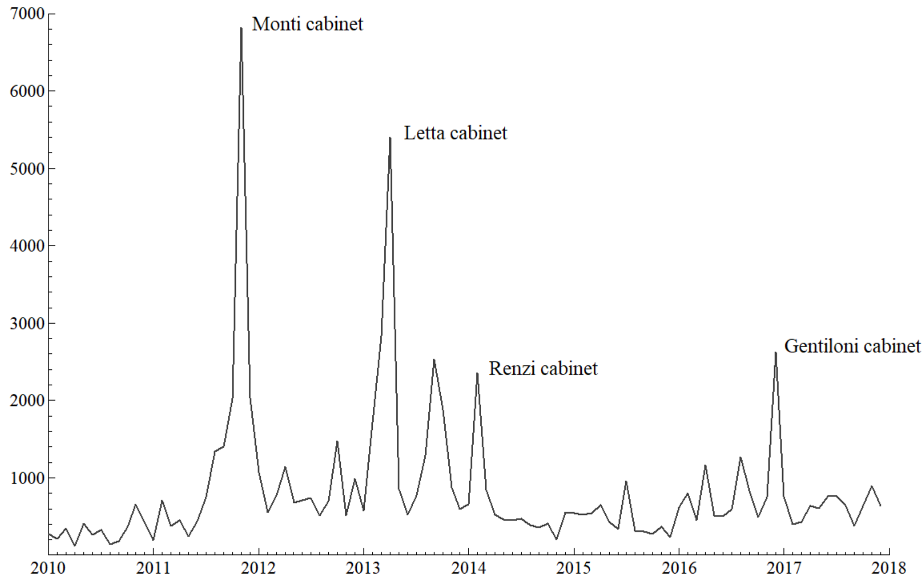

Figure 3.1 – Monthly Number of Tweets

Note: the figure shows the monthly number of tweets that are composed of the keywords "Italian" and "government", from December 2010 to December 2017.

3.3.2 Twitter Political Climate Index

3.3.2.1 Construction: Sentiment Analysis

As defined previously, political climate is the aggregate mood and opinion about a government. In order to proxy political climate, we perform a sentiment analysis on our Twitter data. A sentiment analysis is a procedure that classifies the emotional tone of a text as positive, negative or neutral. We implement a sentiment analysis using a straightforward dictionary-based approach that uses the Harvard-IV general lexicon. The Harvard-IV general lexicon is a list of 3,642 words, 2,005 of which are classified as being negative and 1,637 of which are classified as being positive.

One might ask how a relatively small list of words can adequately categorize the tonality of our dataset. The answer lies in a linguistic concept called the Zipf law, which states that the frequency of any word in a large sample of words is inversely proportional to its rank. The most frequently used word is used twice as often as the second most used word, which is used twice as often as the third most used word, and so on. The Zipf law is itself based on another principle called the "principle of least effort". According to this principle, human beings will tend to use the least amount of effort needed to express a meaning, opinion, or idea. We thus tend to use the same relatively short list of simple words to express ourselves, which explains both why mostly simple words make up the Harvard-IV general lexicon, and why a relatively small list of words is sufficient for our task. The effects of the principle of least effort would seem to be amplified in the context of Twitter, since the number of characters per tweet is limited.

In order to perform the sentiment analysis, we first preprocess the text in the following way: we remove numbers, hashtag signs, mentions, URL and websites. We then convert the text to lower case and replace emojis by their descriptions. For example, we replace the emojis ":)" or ":-)" by the word "smile" and the emojis ":(" and ":-(" by the word "sad".

We construct our political climate index in three steps. First, we measure the sentiment polarity of each tweet. To do so, we compute $polarity_{i,d}$, which is defined as the difference between the number of positive and negative words (term frequencies) that match the Harvard-IV lexicon divided by the total number of words in the tweet:

$$polarity_{i,d} = \left[\frac{\#positive - \#negative}{\text{total \#words}} \right]_{i,d}. \tag{3.1}$$

The indices i and d refer to the tweet i posted on the day d. Thus, $polarity_{i,d}$ gives a sentiment score between -1 and 1. Second, we aggregate $polarity_{i,d}$ on a monthly basis. For this purpose, we create $meanpol_t$ which is the monthly mean of $polarity_{i,d}$ on the month t. Third, we compute the Twitter Political Climate Index (TPCI) by calculating the cumulated sum of the standardized monthly means, as follows:

$$\text{TPCI}_t = \sum_{s=1}^{t} \left(\frac{meanpol_s - \mu(meanpol)}{\sigma(meanpol)} \right), \tag{3.2}$$

where $\mu(meanpol)$ and $\sigma(meanpol)$ are the mean and standard deviation of $meanpol$, respectively.

3.3.2.2 Descriptive Statistics

We now turn to some descriptive statistics about the textual analysis implemented in this section. If we consider a strictly positive (negative) score as measuring a positive (negative) tonality, our polarity index allows us to classify 40 percent of the tweets as positive and 33 percent as negative. The remaining 27 percent of the tweets is considered to be neutral (having a score of 0). The mean of TPCI over our time horizon is -1.52 with a minimum of -5.18 and a maximum of 3.52 (see table C1 in the appendix).

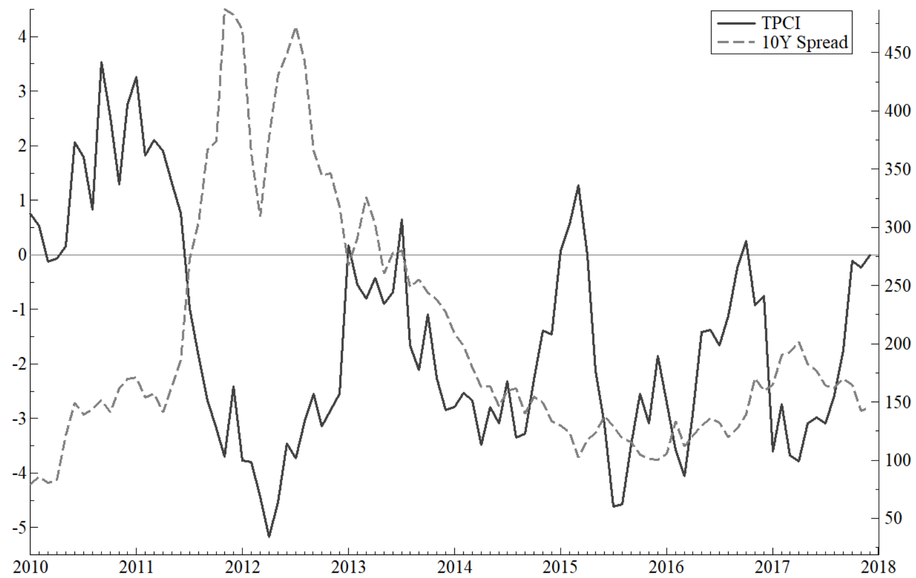

Figure 3.2 – Twitter Political Climate Index (TPCI) and 10-Year Sovereign Bond Spread

Note: the figure shows the Twitter Political Climate Index (TPCI) (plain line) and the 10-year sovereign bond spread (dashed line) of Italy from January 2010 to December 2017. The left y-axis corresponds to the values of TPCI and the right y-axis corresponds to the values of the 10-year sovereign bond spread.

In Figure 3.2, we plot the 10-year sovereign bond spread of Italy against Germany and our political climate index TPCI. We provide more information regarding the construction of the Italian 10-year sovereign bond spread against Germany in the next section of the chapter. The left y-axis of the graph corresponds to TPCI and the right y-axis corresponds to the Italian 10-year sovereign bond spread. We make two main observations. First, we can see a negative correlation between the two series (-0.37) which is in line with our assumption that Italy's political climate is negatively correlated with the pricing of its sovereign debt. Second, we can observe many variations in the two variables. The consistently unstable behavior of TPCI along our time horizon confirms that Italian politics was very unstable between January 2010 and December 2017, as mentioned in section 2. The high volatility in the financial variable from 2010 to 2014 is due to the presence of the European sovereign debt crisis. More information about the macroeconomic and financial variables used in this study are given in the next section.

3.4 Macroeconomic and Financial Variables

This section aims at providing details on the construction and the source of our variables as well as their expected effects on the Italian sovereign bond spread. We describe the Italian sovereign bond spread variable, the proxies for the traditional determinants of sovereign bond spreads, and three more variables that account for the effects of the sovereign debt crisis.

3.4.1 Sovereign Bond Spread

The Italian 10-year sovereign bond spread is the difference between Italy's 10-year sovereign bond yield and Germany's 10-year sovereign bond yield (considered as the less risky sovereign bond). We first compute the daily differential against Germany of the Italian sovereign bond yield using data from Thomson Reuters. We then construct the variable *spread* which is the monthly mean of those daily sovereign bond spreads.

3.4.2 Sovereign Credit Risk

Sovereign credit risk is comprised of three determinants: fiscal conditions, macroeconomic performance and external competitiveness. Fiscal conditions depend on two variables. We work with the current account balance to GDP ratio, measured as differentials versus Germany and at a monthly frequency. The *balance* variable comes from Thomson Reuters and is available on a quarterly basis. We conduct a linear interpolation of this variable to account for the missing values and obtain monthly data. Finally, this variable has been seasonally adjusted with the X-13 ARIMA method using the software JDemetra+.[2] We use this filter-based approach to extract the trend cycle, the seasonal component and the irregular component of a time series so as to remove the seasonality as well as calendar-related movements. The *balance* variable represents the country's external solvency. A large current account balance implies a higher capacity to refinance the country's sovereign debt with trade surpluses. We therefore expect lower value of the current account balance to raise sovereign bond spreads.

Besides this *balance* variable, we also work with the *ltdebt* variable, which represents the proportion of long-term general government debt within the total general government debt. This variable comes from the European Central Bank database. This variable is important for our analysis because the major part of Italy's outstanding government debt is composed of long-term bonds maturing after one year or more. According to Afonso et al. (2015), a country whose debt is primarily long-term is perceived as more creditworthy than a country with debt that will mature in the near future. Therefore, we expect an increase in *ltdebt* variable to reduce the Italian sovereign bond spread.

Second, we proxy macroeconomic performance with the differential versus Germany of the annual growth rate of industrial production. This *production* variable comes from the IMF database and is at a monthly frequency. It accounts for the fact that sovereign bonds are riskier during periods of slow economic growth. Thus, we expect a higher growth rate of industrial production to improve creditworthiness and therefore lower sovereign bond yields.

Finally, we proxy external competitiveness with the CPI based effective exchange rate from the IMF database. This variable accounts for sovereign credit risk coming from general macroeconomic disequilibrium. We have constructed the monthly *exchange* variable by taking the differential against Germany of the log of the real effective exchange rate. This variable allows us to capture the impact of productivity shocks on the economy with respect to Germany. An increase in *exchange* reflects an appreciation in the Italian real exchange

[2] JDemetra+ has been officially recommended since February 2015 for seasonal and calendar adjustment of official statistics by the members of the ESS and the European System of Central Banks.

rate or a depreciation in the German real exchange rate, which we expect to exacerbate the Italian sovereign bond spread.

3.4.3 Sovereign Liquidity Risk

The second main driver, sovereign liquidity risk, is usually assessed using the sovereign bond bid-ask spread, namely the spread between the highest buying price (ask) and the lowest selling price (bid). We obtain the bid and ask prices series from Thomson Reuters. We first compute the daily bid-ask spread i.e. the daily rates of change between the bid and ask prices. We then construct the variable *bidask* which is the monthly mean of those daily spreads and which measures sovereign bond market liquidity. The higher the bid-ask spread, the less liquid the sovereign bond. Therefore, we expect increases in *bidask* to increase the sovereign bond spread.

3.4.4 Global Risk Aversion

The third main driver, global risk aversion, captures the level of perceived global financial risk. To approximate this factor, we first take the S&P 500 stock market implied volatility index (VIX) from Thomson Reuters. We then use the log of this index to create our variable, *vix*. This index tends to increase during periods of bad or uncertain global financial conditions. When *vix* increases, bond investors become more risk averse, which is expected to make sovereign bond spreads surge.

3.4.5 Core-Periphery Heterogeneity

During the sovereign debt crisis, we observe the emergence of a two-speed Europe which translates into a core-periphery heterogeneity. Peripheral countries are more affected by the sovereign debt crisis than core countries, resulting in higher sovereign risk. Although country-specific factors are key drivers of European spreads during the crisis, global co-movements of European sovereign bond yields also play an important role in their evolution because of contagion effects.

To take into account the underlying patterns of the sovereign bond spreads variation, we conduct a principal component analysis on European bond spreads, following Longstaff, Pan, Pedersen, and Singleton (2011) and Afonso et al. (2015). This analysis involves transforming correlated variables into linearly uncorrelated combinations of those variables called "principal components". To conduct this analysis, we perform a principal component decomposition of the correlation matrix of European sovereign bond spreads.

Table C3 presents the results of this principal component analysis. The first principal component captures the variation in the country sovereign bond spread, which is due to the common factor among European spreads. The second principal component captures heterogeneity between countries by assigning positive or negative weights on countries' sovereign bond spreads. We distinguish two groups of countries by the signs of the reported weights. The first group, interpreted as Eurozone core countries, is composed of Austria, Belgium, Netherlands and Finland. The second group represents peripheral countries with higher sovereign risk and is composed of Italy, Spain, Portugal, Greece and France. Therefore, the second principal component captures the discrepancy between the variation of the sovereign bond spreads of core countries and peripheral countries. This component accounts for the fact that the sovereign debt crisis did not impact each European country in the same way, which lead to different levels of sovereign risk between peripheral countries and core countries.

The variable *pc2* corresponds to (minus) this second principal component and captures the core-periphery heterogeneity between Eurozone countries. Following Afonso et al. (2015), we use the negative sign of this variable to simplify the interpretation and account for the fact that countries belonging to the peripheral group present negative weights. Therefore, an increase in *pc2* reflects higher peripheral risk which is expected to amplify the Italian sovereign bond spread.

3.4.6 Central Bank Communication

During the sovereign debt crisis, the European Central Bank intensified its interventions to offset the consequences of the crisis. Those actions, mainly designed to reduce yields of distressed countries, impacted sovereign bond spreads through changes in investors' expectations. We follow the work of Picault and Renault (2017) to account for monetary policy announcements. Picault and Renault (2017) developed their Central Bank Communication Index by studying the content of ECB press conferences' introductory statements and classifying them according to the inclination of monetary policy decisions to be accommodative or restrictive. Following Picault and Renault (2017), we compute our variable *cbci* by taking the difference between the probability of a Hawkish monetary policy and the probability of a Dovish monetary policy. Those probabilities are available every month before January 2015 and every 6 weeks after. Then, for the last three years of the period under study, we conduct a linear interpolation of this variable to account for the missing values. An decrease in this variable indicates that the announced monetary policies are more accomodative, such as debt buyback during financial turmoil, and therefore enhance investors' confidence and result in lower sovereign bond spreads. We thus expect a positive correlation between the *cbci* and the *spread* variables.

3.4.7 Credit Rating

Finally, we consider the effect of sovereign credit ratings as is frequently done in the recent literature. If the sovereign bond market perceives credit ratings to be relevant public information (or news), it could affect the evolution of sovereign bond spreads through changes in expectations. As in Afonso, Furceri, and Gomes (2012), we construct the *rating* variable representing sovereign credit ratings by assigning a numerical note to each rating score to be able to compute the average ratings of the three main agencies (Fitch, Moody's and S&P). A decrease in this *rating* variable implies a deterioration in the long term sovereign debt rating which is expected to increase in sovereign bond spread.

3.5 Empirical Analysis

3.5.1 Unit Root and Stationarity

To test for the presence of unit root in our time series data, we implement two different tests: i) the Augmented Dickey Fuller (ADF) test, ii) the Phillips-Perron (PP) test. Results are shown in Table C4 and Table C5 in the appendix. A variable is considered to be stationary if the stationarity hypothesis is accepted at a five percent level of confidence by both tests. We can thus conclude that $bidask$ is I(0) and that all the other variables of our dataset are I(1). The non-stationarity nature of most of our variables is due to the presence of the European sovereign debt crisis in our time period.

3.5.2 Empirical Strategy

We want to estimate the effect of changes in Italy's political climate on the changes in the Italian 10-year sovereign bond spread against Germany. Our dataset is composed of a combination of stationary and non-stationary time series. A popular model used in this context is the Auto Regressive Distributed Lags model of order p and q (ARDL$(p, q_1, .., q_n)$). This model presents an interesting feature: it provides a straightforward way to cope with long-term interactions by concentrating on the dynamics of a single equation, in which short-run dynamics and long-run relationships are jointly estimated, see Pesaran, Shin, and Smith (2001).

The error correction version of the ARDL$(p, q_1, .., q_n)$ model can be written as:

$$\Delta Y_t = \alpha_0 - \lambda(Y_{t-1} - \theta X_{t-1}) + \sum_{i=1}^{p-1} \psi_i^* \Delta Y_{t-i} + \sum_{i=0}^{q-1} \beta_{i\prime}^* \Delta X_{t-i} + \varepsilon_t, \tag{3.3}$$

where Y_t is our variable of interest, the Italian 10-year sovereign bond spread against Germany, X_t is the set of regressors, λ is the speed-of-adjustment to equilibrium values or the error correction coefficient, and θ denotes the long-run coefficients.

We include in the vector X_t all the variables of our dataset, i.e. TPCI and the traditional determinants of sovereign bond spreads. We use the lag of TPCI in order to avoid a potential reverse causality issue. We also control for sovereign credit risk, sovereign liquidity risk and global risk aversion. More precisely, we include the variables *vix*, *bidask*, *balance*, *ltdebt*, *exchange* and *production*. In addition, we also include *pc2* to capture the core-periphery heterogeneity of the European Monetary Union countries. We slightly diverge from the recent literature studying the determinants of sovereign bonds in that we do not use variables that capture expectations about future levels of debt and balance in percentage of GDP. The reason for that is because of the low frequency of these variables (two observations per year in the case of the ECB database), which is clearly an issue for our study. A way of overcoming this limitation is to use the lag of *balance* and *ltdebt* in order to capture potential expectations about these variables. Finally, we also include two additional variables that control for monetary policy announcements, *cbci*, and for change in notation from credit rating agencies, *rating*.

3.5.3 Results

In Table 3.2, we present the results from estimating equation (3.3). For each estimation, we report the p-values of the Breusch-Godfrey LM test for serial correlation, the White test for heteroskedasticity and the Jarque Bera test for normality. In order to select the best-performing model, we first estimate equation (3.3), removing the non-significant regressors one by one. In column (1), we show the result of this regression. The p-values from the White and Jarque Bera tests indicate the presence of heteroskedasticity and non-normality issues. In Figure C1 provided in Appendix C, we plot the residuals of this regression. We can see that the two largest residuals are in November 2011 and February 2012. These dates are related to two critical moments of the Greek crisis: the proposal for the referendum to accept or refuse a bailout package from the Troika in exchange for further austerity in November 2011, and the announcement of the Second Economic Adjustment Program for Greece in February 2012. Both of these events strongly impacted the contagion effect of the

Table 3.1 – Results With Changes in Italy's Twitter Political Climate Index

		(1)		(2)		(3)	
Error-correction	λ	-0.107***	(0.0228)	-0.0703***	(0.0177)	-0.0703***	(0.0196)
Long-run	vix_t	0.0405***	(0.0134)	0.0513***	(0.0168)	0.0514***	(0.0176)
	balance_{t-1}	1.487***	(0.3889)	1.582***	(0.4917)	1.582***	(0.546)
	cbci_t	0.698***	(0.113)	8.676***	(2.5436)	8.679***	(3.116)
	bidask_t	9.734***	(2.3062)				
Short-run	ΔTPCI_{t-1}	-0.0517**	(0.0211)	-0.0519***	(0.0169)	-0.0519***	(0.0189)
	$\Delta\text{balance}_{t-1}$	-0.215**	(0.0928)	-0.164**	(0.0735)	-0.164***	(0.0593)
	$\Delta\text{ltdebt}_{t-1}$	0.0543**	(0.0273)	0.0618***	(0.0217)	0.0618***	(0.0198)
	$\Delta\text{production}_t$	-0.0425**	(0.0161)	-0.0333**	(0.0126)	-0.0333***	(0.0108)
	$\Delta\text{exchange}_t$			0.203**	(0.0814)	0.203***	(0.0781)
	Δpc2_t			0.143***	(0.0471)	0.143***	(0.053)
Dummies	D2011.11			1.327***	(0.174)	1.327***	(0.0774)
	D2012.02			-0.747***	(0.171)	-0.747***	(0.072)
	Constant	0.229	(0.272)	0.109	(0.209)	0.109	(0.231)
Bootstrap		No		No		Yes	
N		94		94		94	
R^2		0.565		0.743		0.743	
BIC		-0.348		-36.24		-45.33	
RMSE		0.201		0.157		0.157	
Breusch Godfrey		0.154		0.414		0.414	
White		0.00969		0.13		0.13	
Jarque Bera		0.0229		0.0807		0.0807	
Bounds test							
F-stat.		19.690		17.760		57.560	

Note: the dependent variable is the change in the Italian 10-year sovereign bond spread. We use monthly data from January 2010 to December 2017. Standard errors are in parentheses and $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. BIC and RMSE stand for Bayesian Information Criterion and Root Mean Square Error, respectively. The one percent upper-bound critical value for the bounds test to cointegration of column (1) is 5.060. The one percent upper-bound critical value for the bounds test to cointegration of column (2) and (3) is 5.610.

European sovereign debt crisis. For these reasons, we decide to create two dummy variables to control for these two events. The baseline model becomes:

$$\Delta Y_t = \alpha_0 - \lambda(Y_{t-1} - \theta X_{t-1}) + \delta\prime X_t + \sum_{i=1}^{p-1} \psi_i^* \Delta Y_{t-i} + \sum_{i=0}^{q-1} \beta_{i\prime}^* \Delta X_{t-i} + \mu_1 \text{D2011.11}_t + \mu_2 \text{D2012.02}_t + \varepsilon_t. \tag{3.4}$$

Column (2) shows the results from the estimation of the baseline model 3.4. As one can see, including this set of two dummy variables solves both the heteroskedasticity and the non-normality issues (the hypothesis of residuals' normality is accepted at a five percent level of confidence). Moving on to the bounds test to cointegration, we can see that the F-statistics is larger than the one percent upper-bound critical value (17.76 > 5.61), which confirms the

Table 3.2 – Results With Changes in Italy's Twitter Political Climate Index

		(1)		(2)		(3)	
Error-correction	λ	-0.107***	(0.0228)	-0.0703***	(0.0177)	-0.0703***	(0.0196)
Long-run	vix_t	0.0405***	(0.0134)	0.0513***	(0.0168)	0.0514***	(0.0176)
	balance_{t-1}	1.487***	(0.3889)	1.582***	(0.4917)	1.582***	(0.546)
	cbci_t	0.698***	(0.113)	8.676***	(2.5436)	8.679***	(3.116)
	bidask_t	9.734***	(2.3062)				
Short-run	ΔTPCI_{t-1}	-0.0517**	(0.0211)	-0.0519***	(0.0169)	-0.0519***	(0.0189)
	$\Delta\text{balance}_{t-1}$	-0.215**	(0.0928)	-0.164**	(0.0735)	-0.164***	(0.0593)
	$\Delta\text{ltdebt}_{t-1}$	0.0543**	(0.0273)	0.0618***	(0.0217)	0.0618***	(0.0198)
	$\Delta\text{production}_t$	-0.0425**	(0.0161)	-0.0333**	(0.0126)	-0.0333***	(0.0108)
	$\Delta\text{exchange}_t$			0.203**	(0.0814)	0.203***	(0.0781)
	Δpc2_t			0.143***	(0.0471)	0.143***	(0.053)
Dummies	D2011.11			1.327***	(0.174)	1.327***	(0.0774)
	D2012.02			-0.747***	(0.171)	-0.747***	(0.072)
	Constant	0.229	(0.272)	0.109	(0.209)	0.109	(0.231)
Bootstrap		No		No		Yes	
N		94		94		94	
R^2		0.565		0.743		0.743	
BIC		-0.348		-36.24		-45.33	
RMSE		0.201		0.157		0.157	
Breusch Godfrey		0.154		0.414		0.414	
White		0.00969		0.13		0.13	
Jarque Bera		0.0229		0.0807		0.0807	
Bounds test							
F-stat.		19.690		17.760		57.560	

Note: the dependent variable is the change in the Italian 10-year sovereign bond spread. We use monthly data from January 2010 to December 2017. Standard errors are in parentheses and *p<0.1; **p<0.05; ***p<0.01. BIC and RMSE stand for Bayesian Information Criterion and Root Mean Square Error, respectively. The one percent upper-bound critical value for the bounds test to cointegration of column (1) is 5.060. The one percent upper-bound critical value for the bounds test to cointegration of column (2) and (3) is 5.610.

existence of a cointegration relationship between the series under study (see Pesaran et al. 2001 for more details). Furthermore, the error correction coefficient λ is significant and between -1 and 0, which is in line with the conclusion of the bounds test to cointegration. We make several observations about these results.

Most importantly, our results indicate that a one-standard deviation increase in our political climate index is associated with a significant decrease of 5.19 basis points in the 10-year sovereign bond spread of Italy. This result is significant at a one percent confidence level and confirms our assumption that changes in Italy's political climate can predict changes in the pricing of Italian long-run sovereign debt. The special features of the ARDL model allow us to conclude that our TPCI variable has a short-run effect on the Italian long-run sovereign debt.

Furthermore, there are three long-run and six short-run relationships. These coefficients are strongly significant and nine of the eleven have the right signs.

The long-run determinants of the Italian 10-year sovereign bond spread are international risk, *vix*, the central bank communication index, *cbci*, and the trade balance, *balance*. An increase in the vix variable implies a significant increase in the sovereign bond spread, confirming the findings of the literature. The *cbci* index is significantly and positively associated with the the Italian long-run sovereign spreads, as expected. This result is not surprising since the *cbci* controls for both conventional and unconventional monetary policy announcements. Indeed, a number of recent papers have provided evidence that unconventional monetary policies played a crucial role during the European sovereign debt crisis (see among others Corsetti and Dedola 2016, Roch and Uhlig 2018 and Stiefel and Vivès 2019). Counterintuitively, the trade balance has a significant long-run positive effect on the Italian 10-year sovereign bond spread. The fact that this variable has a counterintuitive sign is interesting: there is a strand of the literature on sovereign bonds that suggests that the sovereign bonds of the GIIPS countries have been mispriced since the Great Recession (e.g. De Grauwe and Ji 2012 and Bocola and Dovis 2016). This literature suggests that sentiment and market pessimism, in addition to the traditional determinants, play a role in the pricing of sovereign debt.

In the short run, both changes in $exchange$ and $pc2$ have significant and positive impacts on the Italian 10-year sovereign bond spread. Interestingly, the sign of the trade balance aligns now with the one of the literature: a positive change in this variable is significantly and negatively associated with the pricing of sovereign debt. The variable $production$ has a significant and negative effect on the Italian long-run spread, as expected. *ltdebt* contradicts the results of Afonso et al. (2015) in this regard. Indeed, in their panel estimation, *ltdebt* enters with a significant negative sign. We believe that our result differs from theirs for two reasons: we study a different time period and we focus on a single country. The study of Afonso et al. (2015) uses data from January 1999 to December 2010, which means that

Table 3.3 – Results Without Changes in Italy's Alternative Twitter Political Climate Index

		(1)		(2)	
Error correction	λ	-0.0735***	(0.0185)	-0.0735***	(0.0203)
Long-run	vix_t	0.0495***	(0.0166)	0.0495***	(0.0183)
	$balance_{t-1}$	1.463***	(0.470)	1.463***	(0.534)
	$cbci_t$	8.0856***	(2.420)	8.0856***	(0.980)
Short-run	$\Delta balance_{t-1}$	-0.130*	(0.0763)	-0.130**	(0.0616)
	$\Delta ltdebt_{t-1}$	0.0572**	(0.0227)	0.0572***	(0.0215)
	$\Delta production_t$	-0.0321**	(0.0133)	-0.0321***	(0.0107)
	$\Delta exchange_t$	0.240***	(0.0846)	0.240***	(0.0826)
	$\Delta pc2_t$	0.143***	(0.0494)	0.143**	(0.0559)
Dummies	D2011.11	1.350***	(0.183)	1.350***	(0.0866)
	D2012.02	-0.680***	(0.178)	-0.680***	(0.0767)
	Constant	0.0778	(0.220)	0.0778	(0.260)
Bootstrap		No		Yes	
N		94		94	
R^2		0.713		0.713	
BIC		-30.36		-39.44	
RMSE		0.165		0.165	
Breusch Godfrey		0.816		0.816	
White		0.174		0.174	
Jarque Bera		0.154		0.154	
Bounds test					
F-stat.		16.080		50.230	

Note: the dependent variable is the change in the Italian 10-year sovereign bond spread. We use monthly data from January 2010 to December 2017. Standard errors are in parentheses and $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. BIC and RMSE stand for Bayesian Information Criterion and Root Mean Square Error, respectively. The one percent upper-bound critical value for the bounds test of cointegration of column (1) is 5.610.

they do not take into account the European sovereign debt crisis' critical moments of 2011, 2012 and 2013. In addition, their results are based on a panel data analysis of ten different eurozone countries. We hold that we would have a similar result to theirs if we were working with panel data or studying a country presenting better public finances than Italy. But in the case of Italy, this result is not surprising because the sovereign debt is simply too high. We believe that above a critical level, changes in the maturity structure of the debt are not priced in the same way.

November 2011 is known to be one of the most critical months of the European sovereign debt crisis. The market surge provoked by the proposal for the Greek referendum in November 2011 led the Italian 10-year sovereign bond spread to increase by 132.7 basis points. The announcement of the Second Economic Adjustment Program for Greece in February 2012 'calmed' the market. In this month, the Italian long-run sovereign bond spread decreased by 74.7 basis points.

A potential issue when dealing with relatively small samples (here N=94) is that asymptotic inference may not be reliable since estimators can be biased and standard errors imprecise. When distributional assumptions may not be met, bootstrapping offers a non-parametric strategy to statistical inference. In column (3), we estimate the baseline model using a bootstrap resampling approach with 2000 replications. The bounds test for cointegration confirms the presence of cointegration in our model. One can note that the F-statistic of the bounds test to cointegration of this estimation is much larger than the one of column (2). Furthermore, we can see that the results are very similar to the ones of column (2). The main difference is that the short-run effects of $balance$ and $exchange$ are now significant at a one percent confidence level. Overall, our results suggest that TPCI has a short-run effect on the pricing of long-run Italian debt. More precisely, a positive one standard deviation change in TPCI is associated with a significant decrease of 5.19 basis points in the Italian 10-year sovereign bond spread.

The short-run effect of Italian political climate on the long-run Italian sovereign bond spread can be explained, inter alia, by the "default risk premium channel". Political climate influences the pricing of long-run debt by increasing the perceived probability of sovereign default. It has been shown in several studies that higher political instability and polarization impact the solvency of a country (Brewer and Rivoli 1990 and Van Rijckeghem and Weder 2004). Political instability is one of the most important dimensions of Italian political climate and thus it contributes to Italy's risk of default. When a country is more prone to default, investors are likely to require higher risk premia, which results in higher sovereign bond yield spreads. In addition, investors are likely to reallocate their bond portfolio in this case by selling riskier sovereign bonds in favor of relatively safer ones (the flight-to-safety effect). Therefore, we can posit that a decrease in the Twitter Political Climate Index (representing a deterioration in the Italian political climate) is correlated with an increase in the pricing of sovereign debt because of investors' perception that Italy will default.

We now turn to show to which extent the Twitter Political Climate Index improves the model's predictive power. In Table (3.3), we estimate the baseline model, removing TPCI from the estimation. We estimate the same model in column (1) and column (2), the difference between the two estimations being that the results of column (2) are related to the estimation with bootstrap. We can see that the reported coefficients are in similar orders of magnitude than the ones reported in Table (3.2), even though some of them slightly lose in significance. Let us compare the models' performance by computing the RMSE and the BIC statistics. The RMSE of the baseline model is 0.157 while the RMSE of the estimation without including TPCI is larger: 0.165. In addition, the BIC statistics is the lowest in the case of the benchmark model. These two statistics give strong evidence that Italian political climate provides additional predictive power beyond the traditional determinants of sovereign bond spreads. Our results thus suggest that political factors ought to be taken into account when investigating the pricing of Italian sovereign debt.

3.5.4 Robustness

These results are robust to two robustness checks. We first consider an alternative means of constructing our political climate index. We then control for the number of followers.

3.5.4.1 Alternative Twitter Political Climate Index

Up to this point, we were using the monthly mean of $polarity_{i,d}$ in the construction of TPCI (see equation 3.2). This approach does not take into account the volume of tweets, which can be problematic because it gives a higher (lower) weight to the months with lower (higher) numbers of tweets. To address this issue, we construct an alternative Twitter Political Climate Index, TPCI^{alt}, that controls for both political sentiment and the volume of tweets. To do so, instead of aggregating $polarity_{i,d}$ by computing its monthly mean ($meanpol_t$), we calculate its monthly sum and create the variable $sumpol_t$. Finally, we construct TPCI^{alt}, which consists of the cumulative sum of the standardized monthly sums, as follows:

$$\text{TPCI}_t^{alt} = \sum_{s=1}^{t} \left(\frac{sumpol_s - \mu(sumpol)}{\sigma(sumpol)} \right), \tag{3.5}$$

where $\mu(sumpol)$ and $\sigma(sumpol)$ are the mean and standard deviation of $sumpol$, respectively.

We then estimate equation (3.4) using this alternative Twitter Political Climate Index, TPCI^{alt}. Results are reported in column (1) of Table (3.4). The bounds test to cointegration indicates a cointegration relationship between the series, the F-statistics being larger than the one percent upper-bound critical value. This cointegration relationship is confirmed by the error correction coefficient which is significant and between -1 and 0. We now turn to the results obtained with this alternative Twitter Political Climate Index.

We can see that the coefficient of TPCI^{alt} has a slightly lower magnitude and significance level than those in Table (3.2). In other words, in the short run, a one standard deviation increase in Italy's political climate is associated with a 3.76 basis point reduction in the 10-year sovereign bond spread of Italy. With respect to the initial measure of political climate, the level of significance of TPCI^{alt} drops from one to five percent level of confidence. Our results thus differ from those of Liu (2014). The author only has significant results when considering together volume of tweets and the aggregated sentiment. Our results, by contrast, are significant not only when we consider the volume of tweets and aggregated sentiment together, but also (and even more) when we use the aggregated monthly sentiment by itself.

Table 3.4 – Results With Changes in Italy's Alternative Twitter Political Climate Index

		(1)		(2)	
Error correction	λ	-0.0635***	(0.0188)	-0.0635***	(0.0207)
Long-run	vix_t	0.0563***	(0.0205)	0.0563***	(0.0216)
	balance_{t-1}	1.741***	(0.614)	1.741**	(0.684)
	cbci_t	9.366***	(3.144)	9.366**	(3.808)
Short-run	$\Delta\text{TPCI}^{alt}_{t-1}$	-0.0376**	(0.0181)	-0.0376*	(0.0202)
	$\Delta\text{balance}_{t-1}$	-0.150*	(0.0754)	-0.150**	(0.0601)
	$\Delta\text{ltdebt}_{t-1}$	0.0555**	(0.0223)	0.0555***	(0.0207)
	$\Delta\text{exchange}_t$	0.208**	(0.0844)	0.208**	(0.0821)
	$\Delta\text{production}_t$	-0.0345***	(0.0131)	-0.0345***	(0.0111)
	Δpc2_t	0.139***	(0.0485)	0.139**	(0.0554)
Dummies	D2011.11	1.325***	(0.179)	1.325***	(0.0831)
	D2012.02	-0.744***	(0.177)	-0.744***	(0.0815)
	Constant	0.0964	(0.216)	0.0964	(0.241)
Bootstrap		No		Yes	
N		94		94	
R^2		0.727		0.727	
BIC		-30.67		-39.76	
RMSE		0.162		0.162	
Breusch Godfrey		0.713		0.713	
White		0.169		0.169	
Jarque Bera		0.0917		0.0917	

*Note: the dependent variable is the change in the Italian 10-year sovereign bond spread. We use monthly data from January 2010 to December 2017. Standard errors are in parentheses and *p<0.1; **p<0.05; ***p<0.01. BIC and RMSE stand for Bayesian Information Criterion and Root Mean Square Error, respectively. The one percent upper-bound critical value for the bounds test of cointegration of column (1) is 5.610.*

In addition, the inclusion of TPCI^{alt} does not alter the other variables' signs, but does impact their significance. The level of significance of *production* improves from five to one percent whereas the level of significance of *balance* and *ltdebt* drops respectively from five to ten percent and from one to five percent. Overall, the use of an alternative political climate measure does not alter the global performance of our model very much: the BIC and the RMSE statistics only slightly increase with respect to Table (3.2).

In column (2), we estimate the same model using a bootstrap resampling approach. As in column (1), the bounds test for cointegration as well as the significance of the error correction coefficient confirms the existence of a cointegration relationship between the series. Results from the bootstrap approach are similar in terms of magnitude to the ones reported in column (1). The main difference is a change in the level of significance of some variables. The significance of the TPCI^{alt} variable drops from five to ten percent level of confidence.

These results confirm our hypothesis that Italy's political climate has a short-run effect on the pricing of long-run Italian debt, regardless of the methodology used to proxy political climate.

3.5.4.2 Controlling for the Number of Followers

We now sort the tweets according to the quality of their information. We do this by distinguishing between informed and uninformed users. In their study on the predictive power of Twitter on the dollar/euro exchange rate, Gholampour and Van Wincoop (2017) distinguish between informed and uninformed accounts, setting 500 followers as the threshold at which an account is considered to be informed. Following their example, we compute TPCI_t^{inf} and $\text{TPCI}_t^{inf,alt}$ using the tweets of accounts with 500 or more followers (i.e., of "informed" users), like so:

$$\text{TPCI}_t^{inf} = \sum_{s=1}^{t} \left(\frac{meanpol_s^{inf} - \mu(meanpol^{inf})}{\sigma(meanpol^{inf})} \right), \tag{3.6}$$

$$\text{TPCI}_t^{inf,alt} = \sum_{s=1}^{t} \left(\frac{sumpol_s^{inf} - \mu(sumpol^{inf})}{\sigma(sumpol^{inf})} \right), \tag{3.7}$$

where μ and σ are respectively the mean and standard deviation of the corresponding variables.

We estimate equation (3.4) including these two new indices. Results are shown in Table (3.5), columns (1) and (2). Let us first assess the cointegration relationship between the series under study. In both columns, the F-statistics is larger than the one percent upper-bound critical value (17.79 $>$ 15.38 $>$ 5.61) and the error correction coefficient is significant and between -1 and 0. There is a cointegration relationship between the series and we can now interpret the results.

The use of TPCI_t^{inf} gives results in line with the ones obtained so far in terms of magnitude and significance level. We obtain similar results using $\text{TPCI}_t^{inf,alt}$, apart from its level of significance, which drops from one to ten percent level of confidence. When we include the TPCI_t^{inf} and $\text{TPCI}_t^{inf,alt}$ variables, the macroeconomic and financial variables' sign and significance level remain the same. Overall, controlling for the number of followers does not alter the global performance of our model by much, since the BIC and the RMSE statistics only slightly increase with respect to Table (3.2).

In columns (3) and (4), we estimate the same model as in columns (1) and (2) using a bootstrap resampling approach. The F-statistics of the bounds test for cointegration are much larger than the ones in columns (1) and (2). Together with the significant error correction coefficient, the F-statistics confirms the existence of a cointegration relationship between the series. Results from the bootstrap approach are similar in terms of magnitude to the ones reported in column (1) and (2). Even though all variables are still significant, we note drops and improvements in the level of significance of some variables. The significance of the TPCI_t^{inf} variable drops from one to five percent level of confidence.

These results show that changes in Italy's political climate can predict the Italian 10-year sovereign spread regardless of whether the political climate is derived from informed accounts.

Table 3.5 – Results When Controlling for the Number of Followers

		(1)		(2)		(3)		(4)	
Error correction	λ	-0.0707***	(0.0178)	-0.0642***	(0.0188)	-0.0707***	(0.0196)	-0.0642***	(0.0207)
Long-run	vix_t	0.0506903***	(0.0167209)	.0547512***	(0.0198721)	.0506903***	(.0175616)	.0547512***	(0.0211074)
	balance_{t-1}	1.585136***	(0.4931956)	1.729159***	(0.6055576)	1.585136***	(.5460066)	1.729159 **	(0.6740379)
	cbci_t	8.748493***	(2.564154)	9.373682***	(0.121047)	8.748493***	(3.104895)	9.373682**	(3.776158)
Short-run	$\Delta\text{TPCI}_{t-1}^{inf}$	-0.0485***	(0.017)			-0.0485**	(0.0208)		
	$\Delta\text{TPCI}_{t-1}^{inf,alt}$			-0.0365*	(0.0757)			-0.0365*	(0.0213)
	$\Delta\text{balance}_{t-1}$	-0.159**	(0.0739)	-0.151**	(0.0223)	-0.159***	(0.0594)	-0.151**	(0.0603)
	$\Delta\text{ltdebt}_{t-1}$	0.0620***	(0.0219)	0.0561**	(0.0843)	0.0620***	(0.0202)	0.0561***	(0.0207)
	$\Delta\text{exchange}_t$	0.209**	(0.0819)	0.212**	(0.0132)	0.209***	(0.0785)	0.212***	(0.0818)
	$\Delta\text{production}_t$	-0.0346***	(0.0128)	-0.0362***	(0.0487)	-0.0346***	(0.0109)	-0.0362***	(0.0114)
	Δpc2_t	0.139***	(0.0475)	0.137***	(0.18)	0.139***	(0.0527)	0.137**	(0.0552)
Dummies	D2011.11	1.328***	(0.175)	1.328***	(0.177)	1.328***	(0.0778)	1.328***	(0.0830)
	D2012.02	-0.737***	(0.172)	-0.739***	(0.0183)	-0.737***	(0.0716)	-0.739***	(0.0804)
	Constant	0.127	(0.211)	0.121	(0.217)	0.127	(0.234)	0.121	(0.244)
Bootstrap		No		No		Yes		Yes	
N		94		94		94		94	
R^2		0.739		0.726		0.739		0.726	
BIC		-34.77		-30.3		-43.86		-39.39	
RMSE		0.158		0.162		0.158		0.162	
Breusch Godfrey		0.486		0.704		0.486		0.704	
White		0.143		0.159		0.143		0.159	
Jarque Bera		0.0873		0.0898		0.0873		0.0898	
Bounds test									
F-stat.		17.790		15.380		58.400		48.190	

Note: the dependent variable is the change in the Italian 10-year sovereign bond spread. We use monthly data from January 2010 to December 2017. Standard errors are in parentheses and $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. BIC and RMSE stand for Bayesian Information Criterion and Root Mean Square Error, respectively. The one percent upper-bound critical value for the bounds test of cointegration of column (1) is 5.610.

3.5.5 Political Uncertainty and Business Climate Indices

In this subsection, we compare the performance of our proxy for Italy's political climate with other indices that are partly related to what our political climate index captures. To pursue this test, we check whether a news-based measure of policy uncertainty or proxies for business climate can predict the evolution of sovereign bond spreads.

First, we replace our political climate index by one of the Economic Policy Uncertainty (EPU) indices developed by Baker, Bloom, and Davis (2016). We draw on this index because a wide range of papers have emphasized the significant effect of this EPU index on the financial markets and more specifically on the bond market (see for instance Wisniewski and Lambe 2015, Fang et al. 2017 and Handler and Jankowitsch 2018). In addition to this global EPU index, Baker et al. (2016) have recently constructed country-specific EPU indices. We use the EPU index specific to Italy because the global EPU index could interfere with the effect of the *vix* variable that captures global financial uncertainty. Baker et al. (2016) build their indices by conducting a textual analysis on newspaper articles containing keywords related to uncertainty, the economy, and policy. The Italian EPU index relies on the analysis of two Italian newspapers, Corriere Della Sera and La Repubblica. In line with the literature that emphasizes the link between economic policy uncertainty and the bond market, an increase in the Italian EPU index is expected to increase the Italian sovereign bond spread.

We then estimate equation (3.4) using the Economic Policy Uncertainty index instead of the Twitter Political Climate Index. Results are reported in column (1) of Table (3.6). The bounds test to cointegration indicates a cointegration relationship between the series, the F-statistics being larger than the one percent upper-bound critical value ($15.350 > 5.61$). This cointegration relationship is confirmed by the error correction coefficient, which is significant and between -1 and 0.

We now turn to the results obtained with this EPU Index. We first observe that the coefficient associated with changes in the EPU Index has no statistical effect on the pricing of Italian sovereign spreads, and is close to 0. This result suggests that even though our political climate index may include perceived political uncertainty, our index captures a more broadly-defined political factor than political uncertainty alone. The inclusion of this variable does not change the sign of the macroeconomic and financial variables. The level of significance of *exchange* improves from five to one percent whereas the level of significance of *balance* and *ltdebt* drops respectively from five to ten percent and from one to five percent.

Second, we step away from analyzing political factors and investigate to what extent the business climate can predict changes in sovereign bond spread relative to the political one. We replace our Twitter political climate index with two proxies of the Italian business climate, namely the Business Confidence Indicator (BCI) and the Business Confidence Climate (BCC). We use these variables because political events can affect the business climate and alter investor sentiment through changes in confidence. We obtain the Italian BCI from the OECD database. This indicator is based upon opinion surveys about Italian economic activity such as future production in the industrial sector. Values of this indicator below 100 imply pessimism towards future business performance and values above 100 indicate confidence. The Italian BCC comes from the Italian National Institute of Statistics database (ISTAT) and is calculated by adding together the confidence climates of manufacturing, construction, market services and retail trade sectors. This BCC indicator captures Italian firms' perceptions of the general business situation, including assessments, expectations, opinions and judgments. We thus expect both the BCI and the BCC variables to be negatively correlated with the level of sovereign bond spread.

We then estimate equation (3.4) using the BCI and the BCC variables instead of the Twitter Political Climate Index. Results are reported in column (2) and (3) of Table (3.6). The bounds test to cointegration indicates a cointegration relationship between the series, the F-statistics being larger than the one percent upper-bound critical value ($15.78 > 14.71 > 5.61$). This cointegration relationship is confirmed by the error correction coefficient which is significant and between -1 and 0.

As for the EPU variable, the effect of BCC on the Italian long-run sovereign debt is close to zero and is not significant. The coefficient of the BCI variable enters with a negative sign, which is in line with our expectations. However, this coefficient is not significant. The inclusion of those variables affects the macroeconomic and financial variables' signs and

Table 3.6 – Results With Changes in Political Uncertainty and Business Climate Indices

		(1)		(2)		(3)	
Error correction	λ	-0.0729***	(0.0187)	-0.0726***	(0.0189)	-0.0770***	(0.0189)
Long-run	vix_t	0.049***	(0.0167)	0.0505***	(0.0175)	0.0436***	(0.0159)
	$balance_{t-1}$	1.463***	(0.475)	1.472***	(0.481)	1.339***	(0.443)
	$cbci_t$	8.107***	(2.456)	8.142***	(2.484)	7.429***	(2.271)
Short-run	ΔEPU_{t-1}	0.000192	(-0.0005)				
	ΔBCC_{t-1}			0.0019	(0.0077)		
	ΔBCI_{t-1}					-0.202	(0.208)
	$\Delta balance_{t-1}$	-0.130*	(0.0768)	-0.128	(0.0774)	-0.135*	(0.0765)
	$\Delta ltdebt_{t-1}$	0.0576**	(0.0229)	0.0576**	(0.0229)	0.0539**	(0.023)
	$\Delta exchange_t$	0.244***	(0.0857)	0.237***	(0.0858)	0.242***	(0.0847)
	$\Delta production_t$	-0.0317**	(0.0134)	-0.0321**	(0.0133)	-0.0301**	(0.0134)
	$\Delta pc2_t$	0.141***	(0.0499)	0.143***	(0.0497)	0.141***	(0.0495)
Dummies	D2011.11	1.344***	(0.184)	1.341***	(0.187)	1.336***	(0.183)
	D2012.02	-0.682***	(0.179)	-0.684***	(0.18)	-0.689***	(0.178)
	Constant	0.085	(0.222)	0.0621	(0.229)	0.13	(0.226)
Bootstrap		No		No		No	
N		94		94		94	
R^2		0.713		0.713		0.716	
BIC		-25.98		-25.89		-26.9	
RMSE		0.166		0.166		0.165	
Breusch Godfrey		0.839		0.801		0.891	
White		0.147		0.246		0.192	
Jarque Bera		0.124		0.15		0.289	
Bounds test							
F-stat.		15.350		15.780		14.710	

*Note: the dependent variable is the change in the Italian 10-year sovereign bond spread. We use monthly data from January 2010 to December 2017. Standard errors are in parentheses and *p<0.1; **p<0.05; ***p<0.01. BIC and RMSE stand for Bayesian Information Criterion and Root Mean Square Error, respectively. The one percent upper-bound critical value for the bounds test of cointegration of column (1) is 5.610.*

significance in the same way as EPU. The only exception is the loss of significance of the *balance* variable when we use BCC.

The inclusion of the EPU, BCC or BCI variables slightly deteriorates the global performance of our model with respect to Table (3.2). The BIC statistics (respectively -25.98, -25.89 and -26.9) are larger than the one of the baseline model (-36.24) and the RMSE statistics (respectively 0.166, 0.166 and 0.165) are also larger than the baseline one which is 0.157.

These results suggest that political climate provides additional predictive power to the traditional determinants of sovereign bond spread.

3.6 Conclusion

In this chapter, we study the effects of political climate on the pricing of long-run sovereign debt. Italy's particular social, political and economic organization provides strong grounds for our investigation. What distinguishes our methodology is its simplicity: we gather Twitter data based on only two keywords (Italian and government), and we extract public sentiment using a straightforward dictionary-based approach. Our results show that positive changes in Italy's political climate predict decreases in its 10-year sovereign bond spread. From this we conclude, in line with Liu (2014), that textual data contains information that is not captured by traditional determinants of sovereign bond spread. We also surmise that traditional analyses of sovereign bond spread can be improved through the predictive power of political climate. More broadly, our results suggest that political factors ought to be taken into account when investigating the pricing of sovereign debt. In our current research, we are extending our analysis using factor augmented models to help us reduce the dimensionality of the model without losing useful information contained in sets of key variables.

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General Conclusion

The sub-prime crisis and the recent sovereign debt crisis in Europe have shown that changes in agents' expectations can have significant macroeconomic and financial consequences. Understanding these consequences, studying their origins, and proposing solutions to reduce their negative effects are both major issues of research in economics and major concerns for policy. This thesis interrogates the role of expectations in three different macroeconomic and financial scenarios: chapter one explores self-fulfilling prophecies as a source of fluctuations in business cycles, chapter two investigates how central bank announcements have the capacity to manage market confidence, and chapter three explores how political climate can predict the behavior of financial markets.

This thesis engages a variety of approaches, from theoretical investigation to empirical analysis and techniques taken from the computer sciences, to unearth evidence of different kinds of expectations shocks. The primary contribution of this thesis lies in my conclusion that expectations matter, both for economic research and for sound policy-making.

My first chapter constitutes a theoretical contribution. We provide the first one-sector sunspot model with capacity utilization that replicates both the procyclical co-movement of the main aggregate variables and the hump-shaped response of output (the main stylized fact of a traditional demand shock) when the model is submitted to a pure sunspot shock under realistic parameter values. This chapter brings us one step closer toward solving the puzzle of completely replicating the main stylized fact of a traditional demand shock with a sunspot model. However, the responses are too persistent and not amplified enough to fully replicate the data, showing the failure of one-sector sunspot models with variable capacity utilization to fully replicate all salient features of observed business cycles. This failure provides one possible direction for further research: currently, Dufourt et al. (2017) are investigating whether a two-sector stochastic growth model with variable capacity utilization can be brought in closer proximity to the data.

Chapters two and three both participate in a growing scholarly interest in using textual analysis and other tools from the data sciences to extract information from textual data that are relevant to economic research and policy-making. These chapters show that textual analysis can be profitably used to measure the formation of expectations in a variety of forms: sentiment, confidence, belief, political climate, etc.

I apply the above-mentioned methods to innovative data taken from the social media platform Twitter, albeit in different ways. In chapter two, we use textual analysis and machine learning to proxy belief about the likelihood of a central bank intervention on the sovereign debt market during the European sovereign debt crisis, showing that it is possible to learn from social media data how news announcements are received by the public, and how they impact belief formation. Our methodology outperforms the typical dummy approach of event study analysis by capturing anticipation and delayed reactions that are outside the event window and by distinguishing between the importance of different announcements. The results of our study are in line with the theoretical prediction that the European Central Bank successfully diverted a self-fulfilling default crisis by credibly announcing a policy that was never, in the end, carried out. This event and our analysis of it suggests that further research is merited to measure whether the ECB lost some credibility among market participants by making this announcement but not carrying through. In other words: this strategy worked once, but could it work again? The result of such research could have repercussions for central banks' policies towards announcements. Furthermore, our results suggest that more studies on announcement effects are merited to provide other methodologies that are not based on dummy variables.

In chapter three, we use sentiment analysis techniques to proxy political climate, coming to the conclusion that political climate ought to be considered when investigating the pricing of sovereign debt. Ours is the first study to use Twitter data to investigate the pricing of sovereign bonds over such a long time horizon. This chapter suggests that the predictive power of political climate can improve traditional analyses of sovereign bond spreads. Further research is merited to investigate whether our Twitter political climate index would function for other countries - in France, for instance, during the period of the "yellow vest" protests. In future research, it would also be worth extending our analysis using factor augmented models. Such models would help us reduce the dimensionality of the model without losing useful information contained in sets of key variables.

Chapters two and three provide evidence that social media can be a valuable source of data that can complement surveys or market-based measures. Social media data presents several advantages. First, it is high-frequency data which takes place in "real time". Because this data is produced and accessible immediately, it could be possible, for example, for policy-makers to track the effects of their announcements or changes in policy right away, in complement to market-based measures and without waiting for survey results. Second, social media is a source of data on news, but also on users' opinions on a variety of topics, which makes it a rich source of data for the field of expectations. Similarly, in contrast to surveys, which are costly to design in terms of both time and money, social media data present a way to measure opinions that is not as time consuming. Third, an interesting feature of social media is that users include all types of market participants, including CEOs, policy-makers, institutions, journalists in all different fields, traders, consumers, and so on, which makes its data attractive for economic research in general, and for any type of policy-making.

Social media data present opportunities for research in a number of areas. For instance, this thesis does not directly engage with the literature on "news and noise". This literature suggests that business cycles are the result of signal extraction problems related to the transmission of information about future changes in economic fundamentals. It would be interesting to investigate the presence of news shocks as strictly defined by the news and noise literature through social media data and textual analysis techniques.

The richness of social media data can make it difficult to work with. One direction for future research thus lies in developing tools and methods that allow us to know how to treat this information for different research ends: for instance, by filtering information from social media data by type of market participant. It also goes without saying that social media data contains a lot of noise: it is limited by the presence of bots, and more research is necessary to develop tools that could more efficiently spot and filter out these bots.

Speaking generally, digitalization has transformed societies throughout the globe. It presents individuals with more data, and at a faster pace, than ever before. Naturally, the pace of individuals' decision-making—and, by extension, the pace at which they form expectations and beliefs—is similarly increasing in speed. This profound increase in the speed of expectations-formation is a significant challenge for researchers and policy-makers. We must adapt ourselves to the digital transformation of the world if we are to study expectations in an accurate and relevant way.

While the digitalization of society presents challenges, it also presents researchers and policy-makers with some advantages (which I mention above) for researching expectations and beliefs. This thesis offers a few ways of capitalizing on social media data in the study of expectations. As new tools for extracting and managing social media data continue to be developed, they will allow researchers and policy-makers to better understand expectations and the role they play in economies in the face of digitalization.

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A Appendix to Chapter 1

A.1 Proof of Proposition 1

A steady state is a 4-uple (k^*, l^*, u^*, c^*) such that:

$$Af_1(u^*k^*, l^*)u^*e(u^*k^*, l^*) = \frac{1-\beta(1-\delta^*)}{\beta} \equiv \frac{\theta}{\beta} \quad \text{(A.1a)}$$

$$Af_1(u^*k^*, l^*)u^*e(u^*k^*, l^*) = u^{*\gamma-1} \quad \text{(A.1b)}$$

$$c^* = Af(u^*k^*, l^*)e(u^*k^*, l^*) - \delta^*k^* \quad \text{(A.1c)}$$

$$Bv'(\ell - l^*) = Af_2(u^*K^*, l^*)e(u^*K^*, l^*)u'(c^*) \quad \text{(A.1d)}$$

Using (A.1a) and (A.1b), we find

$$u^* = \left(\frac{\gamma(1-\beta)}{\beta(\gamma-1)}\right)^{1/\gamma}$$

implying

$$\delta^* = \frac{(1-\beta)}{\beta(\gamma-1)}$$

After substitution of this expression into (A.1a), we find that there exists a normalized steady state with $k^* = l^* = 1$ solution of equation (A.1a) if and only if $A = A^*$ with

$$A^* \equiv \frac{\theta}{\beta}\frac{1}{f_1(u^*,1)u^*e(u^*,1)}$$

with $\theta = 1 - \beta(1-\delta^*)$. Including A^* in (A.1c)-(A.1d) and using the share $s = s(u^*, 1)$ of capital income, we find

$$c^* = \frac{\theta - s\beta\delta}{\beta s}, \quad \frac{\theta(1-s)}{s} = \frac{Bv'(\ell-1)}{u'(c^*)}$$

It follows that $(k^*, l^*, c^*) = (1, 1, (\theta - s\beta\delta^*)/s\beta)$ is a normalized steady state solution of the system (A.1a)-(A.1d) if and only if $A = A^*$ and $B = B^*$ with

$$B^* \equiv \frac{\theta(1-s)u'(c^*)}{sv'(\ell-1)}$$

□

A.2 Proof of Lemma 1

Equation (1.12) can be written:

$$Af_1(u_tK_t,l_t)u_te(u_tK_t,l_t)=u_t^{\gamma-1}$$

Solving this equation gives u_t as a function of capital and labor, namely $u_t=\nu(K_t,l_t)$, which allows us to apply the implicit function theorem to compute the following elasticities:

$$\varepsilon_{\nu K}(uK,l)=\frac{\nu_1(uK,l)k}{\nu(uK,l)}=\frac{-\frac{1-s}{\sigma}+\varepsilon_{eK}}{\gamma-1+\frac{1-s}{\sigma}-\varepsilon_{eK}},\quad \varepsilon_{\nu l}(uK,l)=\frac{\nu_2(uK,l)l}{\nu(uK,l)}=\frac{\frac{1-s}{\sigma}+\varepsilon_{eL}}{\gamma-1+\frac{1-s}{\sigma}-\varepsilon_{eK}} \tag{A.2}$$

From (1.2)-(1.3) and recalling that $R_t=1-\delta_t+r_tu_t$, we also derive at the steady state:

$$\begin{array}{ll}\frac{\partial w}{\partial K}\frac{K}{w}=(1+\varepsilon_{\nu K})\left(\varepsilon_{eK}+\frac{s}{\sigma}\right), & \frac{\partial w}{\partial l}\frac{l}{w}=\varepsilon_{el}-\frac{s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\\ \frac{\partial R}{\partial K}\frac{K}{R}=\theta(1+\varepsilon_{\nu K})\left(\varepsilon_{eK}-\frac{1-s}{\sigma}\right), & \frac{\partial R}{\partial l}\frac{l}{R}=\varepsilon_{el}+\frac{1-s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}-\frac{1-s}{\sigma}\right)\end{array} \tag{A.3}$$

We may then compute the following linearized system:

$$\begin{pmatrix}\frac{dK_{t+1}}{K^*}\\ \frac{dl_{t+1}}{l^*}\end{pmatrix}=J\begin{pmatrix}\frac{dK_t}{K^*}\\ \frac{dl_t}{l^*}\end{pmatrix}$$

with

$$J=\begin{pmatrix}1 & 0\\ -\frac{J_{21}}{J_{22}} & \frac{1}{J_{22}}\end{pmatrix}\times\begin{pmatrix}J_{11} & J_{12}\\ -(1+\varepsilon_{\nu K})(\varepsilon_{eK}+\frac{s}{\sigma}) & -\left[-\frac{1}{\varepsilon_{lw}}+\varepsilon_{eL}-\frac{s}{\sigma}+\varepsilon_{\nu K}(\varepsilon_{eK}+\frac{s}{\sigma})\right]\end{pmatrix}$$

where

$$\begin{array}{rcl}J_{11}&=&\frac{\theta}{\beta s}(1+\varepsilon_{\nu K})(s+\varepsilon_{eK})-\delta\gamma\varepsilon_{\nu K}+1-\delta-\varepsilon_{cc}\frac{(\theta-\beta\delta s)}{\beta s}(1+\varepsilon_{\nu K})\left(\frac{s}{\sigma}+\varepsilon_{eK}\right)\\ J_{12}&=&\frac{\theta}{\beta s}\left[\varepsilon_{\nu l}(s+\varepsilon_{eK})+1-s+\varepsilon_{eL}\right]-\delta\gamma\varepsilon_{\nu l}-\varepsilon_{cc}\frac{\theta-\beta\delta s}{\beta s}\left[-\frac{1}{\varepsilon_{lw}}+\varepsilon_{eL}-\frac{s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\right]\\ J_{21}&=&\theta(1+\varepsilon_{\nu K})(\varepsilon_{eK}-\frac{1-s}{\sigma})-(1+\varepsilon_{\nu K})\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\\ J_{22}&=&\theta\left[\varepsilon_{eL}+\frac{1-s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}-\frac{1-s}{\sigma}\right)\right]-\left[-\frac{1}{\varepsilon_{lw}}+\varepsilon_{eL}-\frac{s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\right]\end{array}$$

Therefore

$$\begin{array}{rcl}\mathcal{D}&=&-\frac{J_{11}}{J_{22}}\left[-\frac{1}{\varepsilon_{lw}}+\varepsilon_{eL}-\frac{s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\right]+\frac{J_{11}}{J_{22}}(1+\varepsilon_{\nu K})\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\\ \mathcal{T}&=&\frac{J_{11}J_{22}-J_{12}J_{21}}{J_{22}}-\frac{1}{J_{22}}\left[-\frac{1}{\varepsilon_{lw}}+\varepsilon_{eL}-\frac{s}{\sigma}+\varepsilon_{\nu l}\left(\varepsilon_{eK}+\frac{s}{\sigma}\right)\right]\end{array}$$

Rearranging these expressions leads to the ones expressed in Lemma 1.

□

A.3 Proof of Lemma 2

Straightforward computations give

$$\begin{aligned}\frac{\partial\mathcal{D}}{\partial\varepsilon_{lw}} &= \frac{\frac{\Theta\theta(\gamma-1)(1-s)}{\varepsilon_{\ell w}}\left[1+\sigma\left[(\gamma-1)\beta(1-\delta)+\Theta[1+\sigma(\gamma-1)\beta(1-\delta)]\right]\right]}{\beta\left\{(\gamma-1)[\theta(1-s)+s]+\frac{1}{\varepsilon_{lw}}[\sigma(\gamma-1)+1-s]-\Theta\left[1+\sigma(1-s)(\gamma-1)\beta(1-\delta)+\frac{s\sigma}{\varepsilon_{lw}}\right]\right\}^2} \\ \lim_{\varepsilon_{lw}\to 0}\mathcal{D} &= \frac{1}{\beta}\left[1+\frac{\Theta\theta(\gamma-1)\sigma}{\sigma(\gamma-1)+1-s-\Theta\sigma s}\right]\end{aligned} \tag{A.6}$$

Assumptions 4 and 5 imply $\partial\mathcal{D}/\partial\varepsilon_{lw} > 0$ and $\lim_{\varepsilon_{lw}\to 0}\mathcal{D} > 1$. Moreover, we derive that $\mathcal{D} < 1$ if and only if

$$\Theta > \underline{\Theta} = \frac{(\gamma-1)[\theta(1-s)+s]}{1+\sigma(1-s)(\gamma-1)\beta(1-\delta)}$$

and

$$\varepsilon_{lw} > \underline{\varepsilon}_{ll} \equiv \frac{\sigma(\gamma-1)+1-s-\Theta\sigma s}{[1+\sigma(1-s)(\gamma-1)\beta(1-\delta)](\Theta-\underline{\Theta})}$$

with $\lim_{\varepsilon_{lw}\to\underline{\varepsilon}_{ll}^+}\mathcal{D} = -\infty$. It follows also that when $\Theta\in[0,\underline{\Theta})$ we get, for any $\sigma\in(0,+\infty)$, $1-\mathcal{T}(\sigma)+\mathcal{D}(\sigma)<0$ and $1+\mathcal{T}(\sigma)+\mathcal{D}(\sigma)>0$.

□

A.4 Proof of Proposition 2

Consider equations (A.6). The strategy consists in locating the line Δ_σ in the $(\mathcal{T},\mathcal{D})$ plan. For this we have to precisely locate the initial and final points $(\mathcal{T}(0),\mathcal{D}(0))$ and $(\mathcal{T}(+\infty),\mathcal{D}(+\infty))$. We get

$$\mathcal{D}(0) = \frac{1}{\beta}\frac{[1-\theta(\gamma-1)](\Theta_1-\Theta)}{\Theta_2-\Theta}$$

with

$$\Theta_1 \equiv \frac{(\gamma-1)[\theta(1-s)+s]+\frac{1-s}{\varepsilon_{lw}}}{1-\theta(\gamma-1)} > \Theta_2 \equiv (\gamma-1)[\theta(1-s)+s]+\frac{1-s}{\varepsilon_{lw}} > 0$$

Under Assumptions 4 and 5, we have indeed $1-\theta(\gamma-1)>0$, $\underline{\Theta}<\Theta_2$ and $\Theta_1<\Theta^{max}$. It follows that

- $\mathcal{D}(0)>0$ if and only if $\Theta\in(\underline{\Theta},\Theta_2)\cup(\Theta_1,\Theta^{max})$,
- $\mathcal{D}(0)<0$ if and only if $\Theta\in(\Theta_2,\Theta_1)$.

We also find $\mathcal{D}(+\infty)=1/\beta>1$ and we easily show that

- $\mathcal{D}(0)>\mathcal{D}(+\infty)$ when $\Theta\in(\underline{\Theta},\Theta_2)$,
- $\mathcal{D}(0)\in(0,1)$ if and only if $\Theta\in(\Theta_1,\Theta^{max})$.

Now we can compute

$$1-\mathcal{T}(+\infty)+\mathcal{D}(+\infty) = \frac{\theta(\gamma-1)}{\beta}\frac{\Theta\left[\frac{\varepsilon_{cc}(\theta-\beta\delta s)}{\varepsilon_{lw}}+(1-s)\beta\delta\right]}{\frac{\gamma-1}{\varepsilon_{lw}}-\Theta\left[(1-s)(\gamma-1)\beta(1-\delta)+\frac{s}{\varepsilon_{lw}}\right]}$$

Under Assumptions 4 and 5, we get $1-\mathcal{T}(+\infty)+\mathcal{D}(+\infty)<0$. We conclude therefore that $\mathcal{T}(+\infty)>2$. Similarly, we get

$$1-\mathcal{T}(0)+\mathcal{D}(0) = \frac{\theta(\gamma-1)}{\beta s}\frac{(\theta-\beta\delta s)(\varepsilon_{cc}-\tilde{\varepsilon}_{cc})(\Theta_3-\Theta)}{\Theta-\Theta_2}$$

with

$$\tilde{\varepsilon}_{cc} \equiv \frac{\theta(1-s)}{\theta-\beta\delta s},\ \Theta_3 \equiv \frac{(1-s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)}{\varepsilon_{cc}-\tilde{\varepsilon}_{cc}}$$

and thus $(\varepsilon_{cc}-\tilde{\varepsilon}_{cc})(\Theta_3-\Theta)>0$ if $\varepsilon_{cc}\in(0,\tilde{\varepsilon}_{cc})$. Under Assumptions 4 and 5, we easily derive $\tilde{\varepsilon}_{cc}\in(0,\bar{\varepsilon}_{cc})$ and $\Theta_3>\Theta^{max}$ when $\varepsilon_{cc}\in(\tilde{\varepsilon}_{cc},\bar{\varepsilon}_{cc})$ so that we still get $(\varepsilon_{cc}-\tilde{\varepsilon}_{cc})(\Theta_3-\Theta)>0$. We then conclude

- $1 - \mathcal{T}(0) + \mathcal{D}(0) < 0$ when $\Theta \in (\underline{\Theta}, \Theta_2)$,
- $1 - \mathcal{T}(0) + \mathcal{D}(0) > 0$ for any $\Theta \in (\Theta_2, \Theta^{max})$.

Finally we get

$$1 + \mathcal{T}(0) + \mathcal{D}(0) = \frac{\{2s[1+\beta+\theta(\gamma-1)]+\theta(\gamma-1)[\varepsilon_{cc}(\theta-\beta\delta s)-\theta(1-s)]\}(\Theta-\Theta_4)}{\beta s(\Theta-\Theta_2)}$$

with

$$\Theta_4 \equiv \frac{2s(1+\beta)\left\{(\gamma-1)[\theta(1-s)+s]+\frac{1-s}{\varepsilon_{lw}}\right\}+\theta(\gamma-1)(1-s)(\theta-\beta\delta s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)}{2s[1+\beta-\theta(\gamma-1)]+\theta(\gamma-1)[\varepsilon_{cc}(\theta-\beta\delta s)-\theta(1-s)]}$$

Assumptions 4 and 5 imply

$$2s\left[1+\beta+\theta(\gamma-1)\right]+\theta(\gamma-1)\left[\varepsilon_{cc}(\theta-\beta\delta s)-\theta(1-s)\right] > 0$$

and $\Theta_4 \in (\Theta_2, \Theta_1)$. It follows that

- $1 + \mathcal{T}(0) + \mathcal{D}(0) > 0$ when $\Theta \in (\underline{\Theta}, \Theta_2) \cup (\Theta_4, \Theta^{max})$,
- $1 + \mathcal{T}(0) + \mathcal{D}(0) < 0$ when $\Theta \in (\Theta_2, \Theta_4)$.

From all these information we are then able to derive the following conclusions:

i) when $\Theta \in (\underline{\Theta}, \Theta_2)$, $\mathcal{D}(0) > \mathcal{D}(+\infty) > 1/\beta$, $1 - \mathcal{T}(0) + \mathcal{D}(0) < 0$ and $1 + \mathcal{T}(0) + \mathcal{D}(0) > 0$,

ii) when $\Theta \in (\Theta_2, \Theta_4)$, $\mathcal{D}(0) < 0$, $1 - \mathcal{T}(0) + \mathcal{D}(0) < 0$ and $1 + \mathcal{T}(0) + \mathcal{D}(0) < 0$,

iii) when $\Theta \in (\Theta_4, \Theta_1)$, $\mathcal{D}(0) < 0$, $1 - \mathcal{T}(0) + \mathcal{D}(0) > 0$ and $1 + \mathcal{T}(0) + \mathcal{D}(0) > 0$,

iv) when $\Theta \in (\Theta_1, \Theta^{max})$, $\mathcal{D}(0) \in (0,1)$, $1 - \mathcal{T}(0) + \mathcal{D}(0) > 0$ and $1 + \mathcal{T}(0) + \mathcal{D}(0) > 0$.

Let us finally compute the value σ^H such that $\mathcal{D}(\sigma^H) = 0$. We get the following expression

$$\sigma^H = \frac{(1-\beta)\left[(\gamma-1)[\theta(1-s)+s]+\frac{1-s}{\varepsilon_{lw}}\right]-\Theta[1-\beta-\theta(\gamma-1)]}{(1-\beta)\left\{\Theta\left[(\gamma-1)(1-s)\beta(1-\delta)-\frac{\theta-\beta\delta s}{\varepsilon_{lw}\beta\delta}\right]-\frac{\gamma-1}{\varepsilon_{lw}}\right\}}$$

Under Assumption 4 we have $1 - \beta - \theta(\gamma - 1) < 0$. It follows therefore that $\sigma^H > 0$ if and only if

$$\varepsilon_{\ell w} > \tilde{\varepsilon}_{\ell w} \equiv \frac{\gamma-1+\Theta\frac{\theta-\beta\delta s}{\beta\delta}}{\Theta(1-s)(\gamma-1)\beta(1-\delta)}$$

From now on let us assume that $\varepsilon_{\ell w} > \max\{\tilde{\varepsilon}_{\ell w}, \hat{\varepsilon}_{\ell w}\}$. Denoting $\hat{\Theta} \equiv \Theta_4$, and provided $\mathcal{T}(\sigma^H) \in (-2, 2)$, cases i) and ii) are leading to a localisation of the Δ_σ line as in Figure 1 while cases iii) and iv) are leading to a localisation of the Δ_σ line as in Figure 2.

It remains to show that $\mathcal{T}(\sigma^H) \in (-2, 2)$. Straightforward computations yield

$$\mathcal{T}(\sigma^H) \quad = \quad 2 - \frac{(\theta-\beta\delta s)(1-\beta)(\varepsilon_{cc}-\underline{\varepsilon}_{cc})}{\Theta\beta s\left(1+\frac{\sigma^H}{\varepsilon_{lw}}\right)}(\tilde{\Theta} - \Theta)$$

with

$$\underline{\varepsilon}_{cc} \equiv \frac{\theta(1-s)(\theta-\sigma^H\beta\delta s)}{(\theta-\beta\delta s)\left(1+\frac{s\sigma^H}{\varepsilon_{lw}}\right)}, \quad \tilde{\Theta} \equiv \frac{(1-s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)}{\left(1+\frac{s\sigma^H}{\varepsilon_{lw}}\right)(\varepsilon_{cc}-\hat{\varepsilon}_{cc})}$$

Assumptions 4 and 5 imply $\underline{\varepsilon}_{cc} \in (0, \bar{\varepsilon}_{cc})$ and $\tilde{\Theta} > \hat{\Theta}$. It follows obviously that $\mathcal{T}(\sigma^H) < 2$ when:

- either $\varepsilon_{cc} \leq \underline{\varepsilon}_{cc}$ as in this case we get $(\varepsilon_{cc} - \underline{\varepsilon}_{cc})(\tilde{\Theta} - \Theta) \geq 0$,
- or $\varepsilon_{cc} \in (\underline{\varepsilon}_{cc}, \bar{\varepsilon}_{cc})$ when $\Theta < \tilde{\Theta}$.

Let us then denote

$$\bar{\Theta} \equiv \begin{cases} \Theta^{max} & \text{when } \varepsilon_{cc} \leq \underline{\varepsilon}_{cc} \\ \max\{\tilde{\Theta}, \Theta^{max}\} & \text{when } \varepsilon_{cc} \in (\underline{\varepsilon}_{cc}, \bar{\varepsilon}_{cc}) \end{cases}$$

We then conclude that when $\Theta \in (\underline{\Theta}, \bar{\Theta})$, $\mathcal{T}(\sigma^H) < 2$. Straightforward computations finally also show that $\mathcal{T}(\sigma^H) > -2$.

Solving the equation $1 - \mathcal{T}(\sigma) + \mathcal{D}(\sigma) = 0$ with respect to σ gives the transcritical bifurcation value

$$\sigma^T = \frac{(\theta-\beta\delta s)(1-s)\left(1+\frac{\varepsilon_{cc}}{\varepsilon_{lw}}\right)-\Theta[\varepsilon_{cc}(\theta-\beta\delta s)-(1-s)\theta]}{\Theta s\left[\beta\delta(1-s)+\frac{\varepsilon_{cc}(\theta-\beta\delta s)}{\varepsilon_{lw}}\right]}.$$

which is always positive under Assumption 4. Solving the equation $1 + \mathcal{T}(\sigma) + \mathcal{D}(\sigma) = 0$ with respect to σ gives the flip bifurcation value

$$\sigma^F = \frac{\{2s[1+\beta-\theta(\gamma-1)]+\theta(\gamma-1)[\varepsilon_{cc}(\theta-\beta\delta s)-\theta(1-s)]\}(\hat{\Theta}-\Theta)}{s\left\{2(1+\beta)\left[\Theta\left[(\gamma-1)(1-s)\beta(1-\delta)+\frac{s}{\varepsilon_{lw}}\right]-\frac{\gamma-1}{\varepsilon_{lw}}\right]+\Theta\theta(\gamma-1)\left[(1-s)\beta\delta-\frac{2}{\varepsilon_{lw}}+\frac{\varepsilon_{cc}(\theta-\beta\delta s)}{\varepsilon_{lw}}\right]\right\}}$$

which is positive if and only if $\Theta < \hat{\Theta}$. The conclusions of Proposition 2 then follow from all these results and Lemma 2.

□

B Appendix to Chapter 2

B.1 Figures

B.1.1 Changes in the Belief Indices

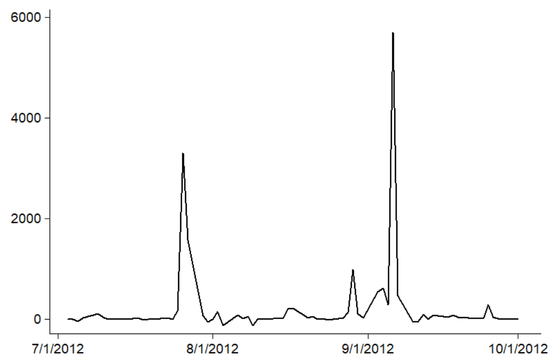


Figure B1 – ΔBelief_t

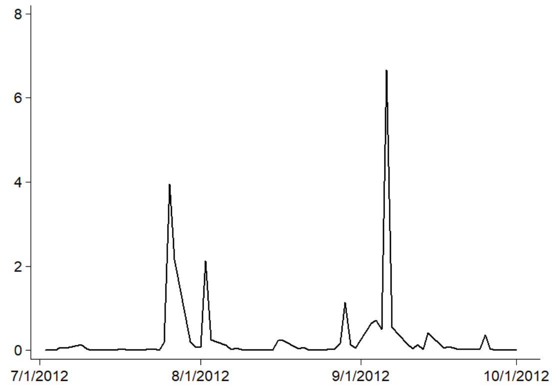


Figure B2 – $\Delta\text{Belief}_t^{alt}$

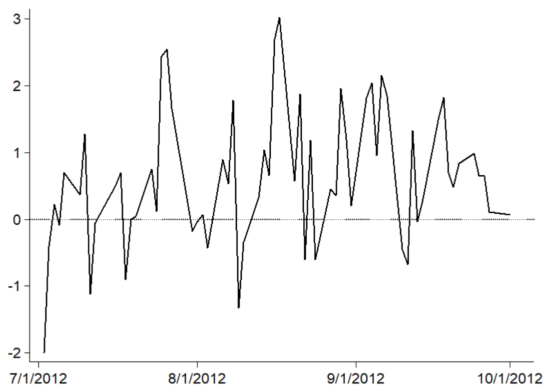


Figure B3 – ΔMean_t

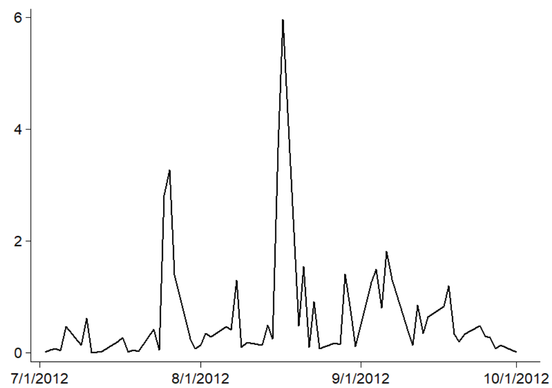
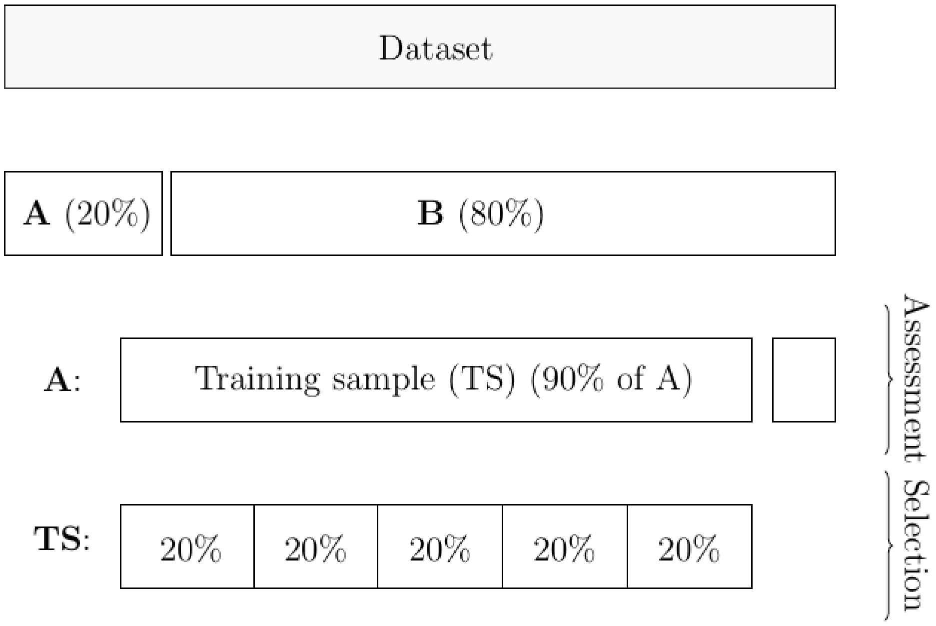


Figure B4 – $\Delta\text{PositiveRatio}_t$

B.1.2 Double Cross-Validation Procedure

Figure B5 – Double Cross-Validation Procedure



Note: this figure shows how our dataset is organized. The tweets in "A" are manually labeled while those in "B" will be predicted by a machine learning classifier. The last two layers describe our double cross-validation procedure. The set "A" is randomly split into a training set (90 percent) and a test set (10 percent). To select our model (to "hypertune" the parameters of the SVM classifier), we proceed with a grid search using a 5-fold cross-validation. The accuracy of the selected model is then assessed on the test set.

B.2 Tables

B.2.1 Examples of Tweets

Table B1 – Examples of Tweets

Text	Label
Draghi's opens door to new ECB policy territory	1
Draghi skips Jackson Hole as ECB shapes bond plans - US News and Wold Report	1
Monti - - Notes Draghi commented on Time Lag Between Govt Action and fall in Spreads and Said ECB may Buy Bonds	1
Reports Of Talks Between Mario Draghi & Bundesbank Head Signal That ECB Measures R 4 Real	1
IMPORTANT..Draghi has opened poss 4 ECB bondbuys w/o EFSF/ESM actually being touched for sov reasons	1
Bloomberg: Draghi said to to give fellow ECB'ers 24 hours +/-s to digest rescue plan before Sept. 6 meeting	1
El Pais:No Taboos at Next ECB Meet:Notes comments from Draghi: they suggest relief measures for Italy & Spain could be on way citing sources	1
No Bazooka As ECB Backtracks: Draghi Won't Pursue Yield Caps, To Sterilize Bond Buys In SMP Continuation	-1
Debt crisis: ECB's Draghi Plan doused by rebellions in Germany and Greece	-1
Super Mario disappoints. Just wondering what Draghi meant by "ready to do whatever it takes to preserve the euro" #ECB talks Italian style..	-1
Global stocks tumble as investors reacted to disappointment that the ECB's Mario Draghi failed to match his words with prompt action	-1
So Draghi says that ECB buying EU member state sovereign bonds is *not* state aid?! Oh sure, whatever you say..	-1
Draghi Overpromised What the ECB Could Achieve	-1
ECB's Draghi gives no hint of bond buys, LTROs	-1
ECB Follows Words With More Words - the market fears Draghi has written a cheque he can't cash	-1
Draghi : "the EURO is irreversible"... again, same speech, no news... #ECB	-1
Sceptics abound as Mario Draghi's ECB bond 'bluff' electrifies global markets	-1
ECB Draghi is useless and his words mean nothing . Eu should break up . Eu does not know what to do at this point.	-1
Draghi says vote not unanimous – there was one dissent. Guess whoooooo? #Germany #ECB	0
All Eyes on ECB's Draghi to Fight Crisis	0
I wonder if economists thought of what comes to everyone's mind when they say Mario Draghi's nickname, Super Mario #ECB #Europe #Eurozone	0
ECB President Draghi Speaks in 4 mins	0
Draghi: economic growth in euro area remains weak #ECB	0
ECB'S DRAGHI: There will be more transparency than before.	0

B.2.2 Summary Statistics for Daily Number of Tweets and ΔBelief_t

Table B2 – Summary Statistics for Daily Number of Tweets

N	Mean	Std.Dev.	0%	25%	50%	75%	100%
66	750	1653	13	93	155	823	9601

Table B3 – Summary Statistics for ΔBelief_t

N	Mean	Std.Dev.	0%	25%	50%	75%	100%
66	231	829	-127	0	22	96	5695

B.2.3 Regression Results for Government Bond Spreads at Lower Maturities

Table B4 – Regression Results for Government Bond Spreads at Lower Maturities

	5-year-maturity			2-year-maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔBelief_t	-0.896			-0.455		
	(0.763)			(0.849)		
ΔBelief_t x Crisis_i	-6.830^{***}			-4.946^{***}		
	(1.119)			(1.245)		
$\Delta \text{Belief}_{t-1}$		-0.274			0.045	
		(0.802)			(0.863)	
$\Delta \text{Belief}_{t-1}$ x Crisis_i		-3.741^{***}	-3.741^{***}		-3.495^{***}	-3.495^{***}
		(1.176)	(0.539)		(1.266)	(0.798)
Time Fixed Effects	No	No	Yes	No	No	Yes
Clustered Standard Errors	No	No	Crisis + Time	No	No	Crisis + Time
Observations	585	585	585	585	585	585
R^2	0.125	0.034	0.394	0.053	0.022	0.262

*p<0.1; **p<0.05; ***p<0.01

Note: the dependant variable is the government bond spread with 5-year and 2-year maturity respectively for all euro area members with available data. $\Delta Belief_t$ is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Ireland, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France and the Netherlands.

B.2.4 Regression Results for CDS Spreads at Lower Maturities

Table B5 – Regression Results for CDS Spreads at Lower Maturities

	5-year-maturity			2-year-maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔBelief_t	−0.552			−0.258		
	(0.461)			(0.674)		
ΔBelief_t x Crisis_i	−5.243***			−5.914***		
	(0.711)			(1.041)		
$\Delta \text{Belief}_{t-1}$		−0.096			0.112	
		(0.487)			(0.691)	
$\Delta \text{Belief}_{t-1}$ x Crisis_i		−3.072***	−3.072***		−4.079***	−4.079***
		(0.752)	(1.057)		(1.067)	(1.255)
Time Fixed Effects	No	No	Yes	No	No	Yes
Clustered Standard Errors	No	No	Crisis + Time	No	No	Crisis + Time
Observations	650	650	650	650	650	650
R^2	0.143	0.042	0.417	0.081	0.033	0.280

*p<0.1; **p<0.05; ***p<0.01

Note: the dependant variable are the CDS spreads with 5-year and 2-year maturity respectively for all euro area members with available data. $\Delta Belief_t$ is the standardized change in the belief index. We use daily data from July 2nd to October 1st. Crisis countries are Ireland, Italy, Portugal and Spain. Other countries in the sample are Austria, Belgium, Finland, France, Germany and the Netherlands.

C Appendix to Chapter 3

C.1 Summary Statistics of TPCI

Table C1 – Summary Statistics of TPCI

	count	mean	sd	min	max
TPCI	96	-1.52359	2.011303	-5.177301	3.527858
TPCI^{alt}	96	-.9982981	3.031163	-7.407921	4.523535
TPCI^{inf}	96	-1.268853	1.84844	-4.833368	3.199636
$\text{TPCI}^{inf,alt}$	96	-1.908992	2.884982	-8.588203	2.430772

C.2 Data Definition and Sources

Table C2 – Data Definition and Sources (Italy, 2010.01-2017.12)

Variable	Description	Source
spread	10 year sovereign bond yield (vs. Germany)	Thomson Reuters
TPCI	Twitter Political Climate Index	1/(Twitter)
$TPCI^{alt}$	Alternative Twitter Political Climate Index	1/(Twitter)
$TPCI^{inf}$	Twitter Political Climate Index with informed accounts	1/(Twitter)
$TPCI^{inf,alt}$	Alternative Twitter Political Climate Index with informed accounts	1/(Twitter)
vix	(Log of) S&P 500 stock market volatility	Thomson Reuters
bidask	10 year sovereign bond bid-ask spread	Thomson Reuters
balance	Current account balance/GDP (vs. Germany)	Thomson Reuters
ltdebt	Long-term/Total general government debt	ECB
exchange	(Log of) CPI based effective exchange rate (vs. Germany)	IMF
production	Industrial production annual growth (vs. Germany)	IMF
pc2	(Minus) Second principal component of spread	1/(Thomson Reuters)
cbci	Central Bank Communication Index	2/
rating	Credit rating (Fitch, Moody's, S&P, Average)	1/
D2011.11	Dummy variable	1/
D2012.02	Dummy variable	1/
epu	Economic Policy Uncertainty Index	3/
bci	Business Confidence Indicator	OECD
bcc	Business Confidence Climate	ISTAT

Note: 1/ Own construction, 2/Picault and Renault (2017), 3/ Baker et al. (2016)

C.3 Principal Component Analysis of European Sovereign Bond Yield Spreads

Table C3 – Principal Component Analysis of European Sovereign Bond Yield Spreads

Nb	Eigenvalues	Cumulative proportion	Eigenvectors (Loadings)	*First principal component*	*Second principal component*
1	0.6096583	0.8904	Spain	0.3202434	-0.4887004
2	0.3975464	0.9346	Portugal	0.3525331	-0.0898689
3	0.1883249	0.9555	Greece	0.33051	-0.0888683
4	0.1538449	0.9726	France	0.3466378	-0.0781213
5	0.1017191	0.9839	Austria	0.341669	0.2794791
6	0.0806428	0.9928	Belgium	0.3518781	0.1791947
7	0.0398023	0.9973	Netherlands	0.3167661	0.1101578
8	0.0246184	1.0000	Finland	0.2953144	0.6612569

C.4 Unit Root Tests and Stationarity

Table C4 – Unit Root Tests and Stationarity, Variables in Levels

Variable	Augmented Dickey Fuller	Phillips-Perron
TPCI	0.1415	0.075
TPCI^{alt}	0.5689	0.4553
TPCI^{inf}	0.1413	0.048
$\text{TPCI}^{inf,alt}$	0.6143	0.4495
spread	0.3483	0.4087
vix	0.2746	0.098
bidask	0.0281	0.0003
balance	0.5069	0.7088
exchange	0.4601	0.3914
production	0.8454	0.7485
pc2	0.0521	0.0559
cbci	0.2556	0.0241
ltdebt	0.4356	0.4083
rating	0.3469	0.4256

Note: the null hypotheses for both tests are the presence of a unit-root. The p-values are reported in this table. For the Augmented Dickey Fuller test, we use two lags on the augmented part. For the Phillips-Perron test, we use the default number of Newey-West lags to use in computing the standard error (three lags).

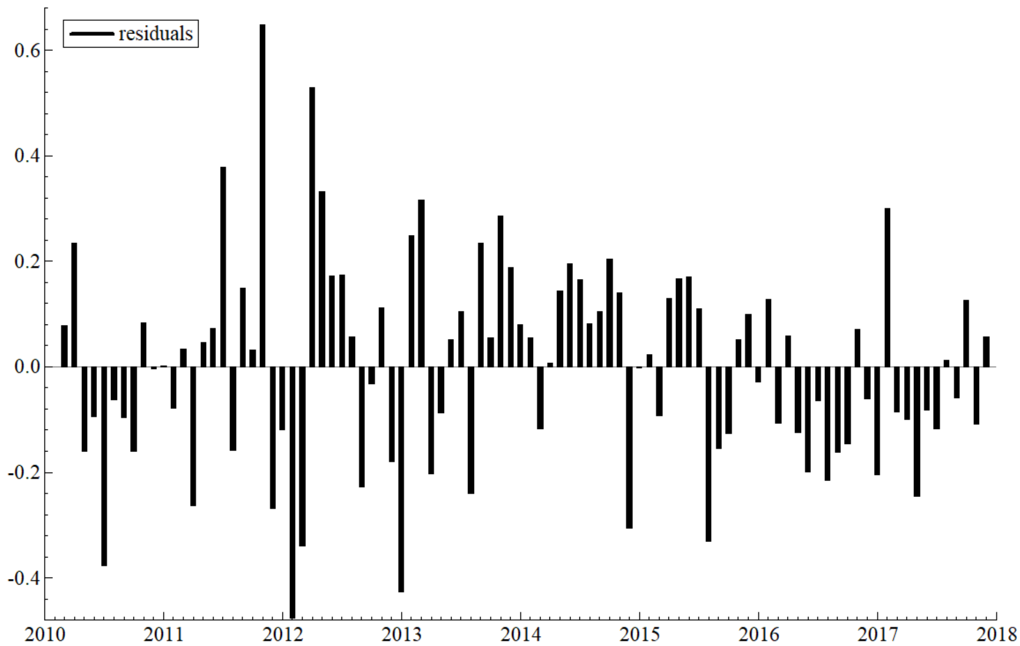
Table C5 – Unit Root Tests and Stationarity, Variables in Changes

Variable	Dickey Fuller	Phillips-Perron
ΔTPCI	0.0000	0.0000
ΔTPCI^{alt}	0.0000	0.0000
ΔTPCI^{inf}	0.0000	0.0000
$\Delta\text{TPCI}^{inf,alt}$	0.0000	0.0000
Δspread	0.0000	0.0000
Δvix	0.0000	0.0000
Δbalance	0.0000	0.0000
Δexchange	0.0011	0.0000
Δproduction	0.0000	0.0000
Δpc2	0.0000	0.0000
Δcbci	0.0000	0.0000
Δltdebt	0.0000	0.0000
Δrating	0.0053	0.0000

Note: the null hypotheses for both tests are the presence of a unit-root. The p-values are reported in this table. For the Augmented Dickey Fuller test, we use two lags on the augmented part. For the Phillips-Perron test, we use the default number of Newey-West lags to use in computing the standard error (three lags).

C.4.1 Residual Plot

Figure C1 – Residual Plot



Abstract

In this thesis, I investigate the role of expectations in business cycles by studying three different kinds of expectations. First, I focus on a theoretical explanation of business cycles generated by changes in expectations which turn out to be self-fulfilling. This chapter improves a puzzle from the sunspot literature, thereby giving more evidence towards an interpretation of business cycles based on self-fulfilling prophecies. Second, I empirically analyze the propagation mechanisms of central bank announcements through changes in market participants' beliefs. This chapter shows that credible announcements about future unconventional monetary policies can be used as a coordination device in a sovereign debt crisis framework. Third, I study a broader concept of expectations and investigate the predictive power of political climate on the pricing of sovereign risk. This chapter shows that political climate provides additional predictive power beyond the traditional determinants of sovereign bond spreads. In order to interrogate the role of expectations in business cycles from multiple angles, I use a variety of methodologies in this thesis, including theoretical and empirical analyses, web scraping, machine learning, and textual analysis. In addition, this thesis uses innovative data from the social media platform Twitter. Regardless of my methodology, all my results convey the same message: expectations matter, both for economic research and economically sound policy-making.

Keywords: expectations; business cycles; self-fulfilling prophecies; central bank announcements; sovereign debt crisis; unconventional monetary policy; credibility; political climate; sovereign bond spread; theoretical analysis; empirical analysis; Twitter data; web scraping; machine learning; textual analysis

Résumé

Cette thèse étudie le rôle des anticipations dans les cycles économiques en analysant trois types d'anticipations différentes. Dans un premier temps, je me concentre sur une explication théorique des cycles économiques générée par des changements d'anticipations qui se révèlent auto-réalisatrices. Ce chapitre contribue à améliorer un puzzle provenant de la littérature sunspot, soutenant ainsi une interprétation des cycles économiques basée sur les prophéties auto-réalisatrices. Dans un deuxième temps, j'analyse empiriquement comment les annonces de la banque centrale se propagent à l'économie via la modification des croyances des acteurs du marché. Ce chapitre montre que des annonces crédibles sur les futures politiques monétaires non conventionnelles peuvent être utilisées comme un instrument de coordination des anticipations dans un contexte de crise de la dette souveraine. Dans un troisième temps, je m'intéresse à un concept plus large d'anticipations et étudie le pouvoir prédictif du climat politique sur la tarification du risque souverain. Ce chapitre montre que le climat politique apporte un pouvoir prédictif supplémentaire aux spreads des obligations d'Etat, au-delà des déterminants traditionnels. Afin d'étudier le rôle des anticipations dans les cycles économiques, différentes méthodologies sont utilisées dans cette thèse, notamment des analyses théoriques et empiriques, du web scraping ainsi que des méthodes d'apprentissage automatique et d'analyse textuelle. Par ailleurs, j'exploite dans cette thèse des données innovantes provenant du réseau social Twitter. Quelle que soit la méthodologie employée, tous mes résultats transmettent le même message: les anticipations comptent, tant pour la recherche en économie que pour l'élaboration de politiques économiques.

Mots-Clés: anticipations ; cycle économique ; prophéties auto-réalisatrices ; annonces de la banque centrale ; crise de la dette souveraine ; politique monétaire non conventionelle ; crédibilité ; climat politique ; obligations d'Etat ; analyses théoriques et empiriques ; données Twitter; web scraping ; apprentissage automatique ; analyse textuelle