The PIIGS Acronym as Heuristic Device during the European Sovereign Bond Crisis

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1 Introduction: Argument and contribution

How do financial investors assess a country's default risk? Once relegated to the political economy of emerging markets, the European Sovereign Bond crisis has reignited interest in this question even in the context of relatively rich economies. Building on a decades-long literature in economics and political science, a plethora of economic and political factors, both country-specific and global, have been proposed and empirically tested as determinants of sovereign bond interests (e.g. Bechtel 2009, Mosley 2003). At the same time, scholars have been investigating how investors weight the above mentioned risk factors about a given sovereign to infer the default risk of *other* somehow related countries. Alongside a renewed interest in standard models of "contagion effects" in financial markets (e.g. Pragidis et al. 2015), a more recent wave of scholarship has focused on the "peer effects" of socially constructed categories (Fourcade 2013). Conceptualizing categorizations and classifications as cognitive decision-making shortcuts opens up the possibility that these heuristic devices may not be just neutral representations of economic fundamentals, but may exert an independent effect on investors' asset allocation decisions (Brooks et al. 2015, Brazys and Hardiman 2015). In this paper, I investigate whether and to what extent the use of the PIIGS acronym[1] (Portugal, Italy, Ireland,

[1]In this first iteration of the paper I do not include Portugal simply due to time constraints

Greece and Spain) in the media acted as a mechanism of contagion and explains sovereign interest variations during the European Sovereign Bond crisis beyond domestic and global factors. In doing so, the paper offers two major contributions. First of all, the paper contributes to the literature on peer effects and diffusion in international financial markets providing new evidence for "peer group" effects beyond the context of emerging economies (e.g. Brooks et al. 2015, Linsi and Schaffner 2019). Second, I provide evidence of one specific mechanism through which "peer group" effects take place, i.e. the use of group acronyms by the media. In so doing, the paper contributes to the broad literature on financial contagion by identifying an additional transmission channel that complements the often explored trade and financial mechanisms (Pentecost et al. 2019, Neri and Ropele 2015).

The paper is organized as follows. First, I will review the literature on cognitive shortcuts and the performative role of ideas in political science - with a particular focus on the political economy of finance - as well as the literature on financial contagion and the role of the media. Second, I will give a brief overview of how the acronym PIIGS became popularized in the media. Then, I will introduce the theoretical framework, inspired by the behavioral finance literature. I will underline two broad mechanisms through which the continued use of grouping acronyms may affect investors' behavior - the representativeness bias and availability bias - and propose two main hypotheses linking financial market reactions to the usage of the PIIGS acronym in the media. In so doing, I will also set expectations about heterogeneous effects across the countries under study (distinguishing between Greece, on the one side, and the other countries). The following section will detail the research design, with a particular emphasis on the measurement strategy, the sample and variable selection, and the statistical methodology. The statistical methodology section is further divided into subsections, the most important of which concerns the two distinct identification strategies employed (recursive identification and sign restrictions). Finally, I will (very briefly, for now) discuss the results and underline the robustness checks I have undertaken (or I plan to do in the next iteration of the study).

2 Literature Review

2.1 Cognitive Shortcuts and the Performative Role of Ideas

The study of categories and classifications is by no means a novel development in the social sciences (Fourcade and Healy 2017). The ways in which categories embody vocabularies, nomenclatures, and meanings that enable and sustain social life and help individuals grasp the world around them has been a central theme in the social sciences since Durkheim (Schmaus 2004). Recent years have witnessed a revival in this long scholarly tradition and a renewed interest in the role of of classifications and categorizations in micro-economic settings, such as the wine market (Diaz-Bone 2017), the US subprime credit sector (Rona-Tas 2017), social investments (Nagel et al. 2017) and the fashion world (Schiller-Merkens 2017). At the same time, scholars in political economy in particular have started exploring this perspective in broader macro contexts, usually focusing on capital markets (Brazys and Hardiman 2015, Brooks et al. 2015, Wansleben 2013), but also on foreign direct investments (Linsi and Schaffner 2019)

What these studies usually have in common is the view that categorizations/classifications transcend their prima facie descriptive character to produce (and reproduce) value judgements about the categorized/classified. These, in turn, may have tangible material consequences (Fourcade 2016). More specifically, why should simple acronyms work as a mechanism of market sentiment diffusion? After all, one may argue that group acronyms simply reflect underlying similarities in economic and/or political fundamentals. While this might explain why a given acronym (e.g. BRICs, LDCs, PIGS, PIIGS) came into being in the first place, scholars and practitioners have often found a good degree of arbitrariness in these categorizations (O'neill 2011, Wansleben 2013). Moreover, the possibly objective origin of these classificatory regimes does not exclude the possibility that its continued use in the public sphere might have real consequences for the countries in questions by shaping the way we talk about, and thus think of them (Brazys and Hardiman 2015). As Marion Fourcade aptly puts it:

"Who would you rather put your money on – the BRICs or the PIGS? The terms (which evocate, respectively, a sturdy material and a filthy porcine) are not irrelevant here: we think and feel through language" (Fourcade 2013). In this sense, and not unlike the BRICs acronym, the PIIGS heuristic can be seen as a tool in the "classificatory regime of international finance" that may shape, and not only reflect, investment patterns (Wansleben 2013). In this sense, while acronyms are only one of many possible heuristics economic agents rely on (e.g. Gray 2013), they can be interpreted as an example of how political-economic orders becomes intertwined with economic-related knowledge and information.

In this sense, the use of heuristics can be linked to another strand of the literature, which emphasizes the performative role of idea in shaping political-economic decisions (Blyth 2003; Best 2018; Chwieroth 2009). Without denying the importance of material factors, scholars in this tradition have drawn from insights in sociology, psychology, and behavioral economics to argue that beliefs about the world are "sticky" and relatively inelastic to dis-confirming evidence (e.g. Hall 2013). In particular, the accentuation (minimization) of perceived differences between (within) the group in order to make sense of an information-rich environment leads the way to a possibly enduring performative role of stereotypical categorizations and classifications (Taylor and Hamilton 1981). From this perspective, agents' reliance on heuristic devices is related to the need to overcome problems of incomplete information by translating unmeasurable "Knightian" uncertainty into quantifiable risk in a conveniently quick fashion (LeRoy and Singell Jr 1987). This way, economic agents obviate the costs of collecting complete information and of solving complex decision making processes (Simon 1990, Kahneman and Tversky 2013). In other words, these heuristics offer the promise of being "good enough" (Brooks et al. 2015) or, to use Simon's (1990) famous terminology, "satisficing". Moreover, as it is well known in the asset price literature, the importance of heuristic devices increases during economic/financial turmoil (e.g. Stracca 2004; Rigotti and Shannon 2005). During these periods - characterized by heightened uncertainty - rational optimization becomes more complex and time-consuming (Büchel 2013).

Within these frameworks, political economists have shown particular interest in investigating the use of heuristics in financial markets. In an early study, Mosley (2003) showed that sovereign bond investors utilize distinct indicators to assess the creditworthiness of developed and developing countries. In particular, investors tend to focus on a "narrow" range of government policies in the former case, and a "broad" set of indicators in the case of developing countries. More recently, Julia Gray (2013) has shed light on how a country's membership in international organizations functions as a heuristic device to infer its economic prospects. Likewise, Brazys and Hardiman (2015) investigate how Ireland's discursive inclusion in the PIIGS acronym affected financial market's perception of the country's creditworthiness, while Brooks et al. (2015) have found similar results looking at different country groupings in the case of emerging markets. Finally, Linsi and Schaffner (2019) have drawn the attention to the scope conditions of investment heuristics showing that they are more likely to affect short-term equity investments rather than long term foreign direct investments.

What have we learned from the extant literature? Scholars from a variety of disciplines have convincingly shown how and when social categories can have a performative role. Nevertheless, most of these studies have focused on micro-economic market settings (mostly in the sociological literature) or, when concerned with broader macro-contexts, on emerging economies (e.g. Brooks et al. 2015, Gray 2013). Since poorer, non-Western countries are most often the target of categorizations (e.g. Third World, emerging economies, frontier economies, LDCs, BRICs etc)(Mosley 2003), we still lack an empirical application to rich(er) countries.[2] The recent European Sovereign debt crisis - with its stark North-South, creditor-debtor cleavages - offers fertile ground for an empirical application. Moreover, and notwithstanding the methodological richness of previous studies, relevant questions pertaining misspecification and reverse causality in single-equation models loom large. For example, Linsi and Schaffner (2019) explicitly qualify their results against a causal interpretation on the ground that their single equation model (following Brooks et al. 2015) does not account for reverse relationships.

[2]One exception is Brazys and Hardiman 2015 who focus on one country only, though (Ireland)

2.2 Financial Contagion and the Role of the Media

Clearly, the literature on financial contagion as well as that on the role of the media in financial markets are too vast to be reviewed here. As such, I will focus mostly on the applications to the recent European financial crisis. Moreover, in this paper, I wish not to enter into the details of the (largely) theoretical debate in financial economics about the differences between contagion and spillover. The distinction is tenuous at best, and model-dependent at worst (Rigobon 2019). As such, I follow Rigobon (2019) and use the words contagion and spillover interchangeably to describe the phenomenon of transmitting a shock from one country to another.

First, a long-standing literature in economics has studied contagion as a degenerate form of interdependence (Cronin et al. 2016). In these studies, scholars usually assess contagion by looking at the degree of correlation between different assets (or similar assets originating from different entities) and, possibly, how they change over time (Bird et al. 2017). An example of such study in political science is that of Brooks et al. (2015), where the contagion variable is operationalized as a weighted average of the other countries in a given category. In the EU context, Missio and Watzka (2011) find evidence of increased correlation between Greek risk premia and those of other European countries at the beginning of the crisis and Muratori (2015) presents similar evidence for the entire period. Not everyone agrees, though. In stark contrast with the previous works, Pragidis et al. (2015) find that the correlation between Greek interest risk premia and those of other countries even decreased after 2009, while Philippas and Siriopoulos (2013) also find no evidence of contagion among peripheral European countries. Other scholars have tried to differentiate between types of financial contagion. In a influential study published at the peak of the European crisis Giordano et al. (2013) find evidence of so-called "wake up" contagion, the situation when an unexpected event in one country (Greek crisis outbreak, in this case) heightens investors' attention about other countries' fundamentals, thus leading to a revision of their previous default risk assessment[3].

[3]Traditionally, the finance literature distinguishes between wake-up-call contagion, shift contagion, and pure contagion (Eichengreen et al. 1996). Shift contagion is analogous to wake up call contagion although the increased sensitivity is due to common rather than country-specific factors. Pure contagion is the residual category that covers situations

All in all, while there is no consensus on the presence (and above all the size) of financial contagion during the European crisis (e.g. Aizenman et al. 2013), most studies do find evidence of some patterns of contagion, although they may differ when it comes to the specific channels - such as trade and financial linkages - through which contagion takes place (Pentecost et al. 2019). As Forbes and Rigobon (2002) notice, though, one possible weakness of these studies is that the co-movement of financial assets may be due to a third broader (regional or global) factor.

Partly as a reaction to this methodological weakness, another strand of the literature has emphasized the need to look at exogenous events to infer genuine contagion. These studies often look at the financial markets effects of discrete events such as scheduled-ahead EU summits (Smeets and Zimmermann 2013) or foreign country-specific news (Bahaj 2020) that are plausibly orthogonal to the target country's economy[4]. With some exceptions (CIT), scholars adopting this strategy have also found evidence of contagion, mostly, but not exclusively, among peripheral European countries. For example, in a highly influential study, Mink and De Haan (2013) show that news about a bailout of Greece (and only Greece) had an effect on the sovereign bond prices of other Southern economies. Likewise, Corbet (2014) shows how rating agencies' downgrading announcements had a contagion effects on other EU countries. While these studies provide valuable insights about the causal nature of contagion, they are limited to discrete well recognizable events and thus may not be generalizable to the day-to-day operations of financial markets.

Finally, and as some of the studies mentioned above show, a few scholars have explicitly linked contagion effects to the role of the media[5]. Intuitively, news releases represent a change in the agents' information set and, if not foreseen, should affect yields (Caporale et al. 2018). For example, Beetsma et al. (2013) find that the amount and tone of news related to a PIIGS country raises the spread of the other group members and even, albeit to a lesser extent, that of other European countries. Similarly,

when contagion is completely unrelated to both levels and changes in fundamentals. As most studies find little evidence for pure and shift contagion (e.g. Giordano et al. (2013), Caporin et al. 2018), I restrict my discussion to wake-up-call contagion.

[4]As it will become clear later, I will use the terminology "target" country throughout the paper to refer to the country about which investors make their evaluation/assessment.

[5]Notice that while the literature on the media and financial markets is incredibly vast, fewer studies explicitly investigate the media as a possible mechanism of contagion

Caporale et al. (2018) find similar evidence for a longer period and show the correlation to be stronger during high volatility periods and especially in the EU periphery.

What have we learned from these insights? By and large, most (but not all) studies have detected one form or another of contagion. As Pentecost et al. (2019) note, though, less is known about the factors underlying financial contagion beyond the financial and trade transmission mechanism. Indeed, a major contribution of the present study is not only to provide further evidence of financial spillover but also to investigate the importance of a novel channel through which it takes place, i.e. investors' reliance on grouping acronyms in the media as a heuristic device to infer a country's future prospects. Though, before elaborating on the theoretical expectations, a brief digression on the origin of the PIIGS acronym seems in order.

3 A brief story of the PIIGS acronym

The original acronym, PIGS, emerged in the mid-90s during the negotiations over the conditions to enter the European Monetary Union, although the idea of Southern European economies representing a well defined socio-economic cluster with a pejorative connotation had already been around for some time (Brazys and Hardiman (2015)). Apparently, the first use of the term in print was a *Wall Street Journal* article in 1996. Interestingly, applying text analytical and topic modeling techniques to German news media, Küsters and Garrido (2020) find that the heuristic was initially shaped by socio-cultural attributes that mainly reflected the experiences of tourists, and was only subsequently attached to an economic dimension. This descriptive finding is in line with the previously reviewed literature on classifications/categorizations as cultural templates that convey stereotypical value judgements (Fourcade 2013). In so doing, the acronym has transcended its economic meaning and arguably played a role in reviving *essentialist topoi* that degraded peripheral EU states as backward, lazy, irrational, corrupt, inefficient and wasteful (Küsters and Garrido 2020). According to some, the acronym PIIGS transforms the dividing line between debtors and creditors into a morally charged one of saints and sinners (Dyson 2014)[6].

Finally, it should be noted that PIIGS (as opposed to, for example, BRICs) is a particularly tough case to test the effects of acronyms as heuristic device. Indeed, the term was used less than it probably would have been because of the decision of news media and institutions such as the Financial Times and Barclays Capital to ban its use in print due to its perceived offensiveness (Dooley 2019).

4 Theory and Hypotheses

Standard economic models assume that agents possess computational capabilities that are at odds with empirical psychological findings (Conlisk 1996). By contrast, behavioral scholars argue that agents often employ mental shortcuts and "rules of thumb" to optimize deliberation costs. These specific shortcuts are often referred to as decision heuristics (Kahneman and Tversky 2013). Such heuristics, while individually rational, may lead to poor aggregate decision-making as they involve "blunders" that would otherwise be avoided if agents were to engage in a full cost-benefit analysis (Stracca 2004). Within the decision heuristics identified in the literature (for an overview see Stracca 2004), two specific blunders seem particularly relevant in this context: the representativeness bias and the availability bias.

Originally proposed in the classic study by Tversky and Kahneman (1974), the repsentativeness and availability heuristics are particularly useful to understand how people reason about uncertain events.[7] Agents subject to the reprsentativeness heuristic evaluate the probability that an element A belongs to a class B by examining the degree to which A is *representative* of B, i.e. how much A resembles B. Then, agents simply assign high (low) probability of A belonging to B if A is similar (dissimilar) to (from) B. In our case, the class is "default/untrustworthy type" (in terms of default risk) and each country is a (possible) element[8]. The contention here is that the inclusion of a country

[6] A similar, but opposite, essentialist narrative was also present in debtor countries against Northern creditors (Adler-Nissen 2017)

[7] This section borrows heavily from Tversky and Kahneman (1974)

[8] While at the beginning of the crisis the Greek government was clearly viewed as the prototypical default type, all these countries' governments were viewed as such, albeit to different extents, as the crisis unfolds. Hence, I keep the more general "default/untrustworthy type" label although, at the beginning of the crisis, the real question could also

in the acronym PIIGS functions as a signaling mechanism about the government's type.

The more the PIIGS acronym is being used, the more its constitutive members are discursively linked together. In turn, such discursive proximity will result in agent's perceptions of the countries as a bloc. The more country X is discursively associated to the PIIGS group (i.e. the more the PIIGS acronym is being used), the more investors will be sensitive to developments in country X to infer future policies and performances of the remaining members.

While relying on such stereotypical reasoning is not without value at times (to state otherwise would be equivalent to assume that investors can never learn anything about A unless it comes solely from A), it may also lead to sub-optimal outcomes. The main reason is that, while somehow informative, representativeness is independent of (thus, unaffected by) other factors that should influence our assessment of the probability of interest.

One prominent factor is the baseline probability of the event of interest (priors). Indeed, what investors need to known is not simply how A is representative of B but also how likely B is to begin with. As the ultimate goal is to avoid losing money by investing in a country that may default, one should weight the probability of being part of a untrustworthy group by the baseline probability of default actually taking place. In other words, the representativeness heuristic is a classic violation of Bayes' theorem, as it leads agents to equate inverse probabilities (the Pr(default given PIIGS) = Pr(PIIGS given default) without accounting for the Pr(default)). Such neglect is potentially very important in our case as we know that - prior to the crisis - investors, practitioners, and scholars alike assigned an extremely low baseline probability of sovereign default in an OECD countries (Mosley 2003).

A related factor that should affect a fully Bayesian actor's assessment of probabilities and that is arguably at play here is sample size. Indeed, while the prior probability of a rich country's default was viewed as extremely low at the start of the crisis, investors should have rationally updated their prior upwards as the crisis unfolded. In other words, the experience of Greece - a relatively rich, Western,

be interpreted as: "how much does A's government resemble the Greek government?"

OECD country - in the first year of the crisis showed the prior baseline assessment to be off the mark. Nevertheless, the more interesting question is: *by how much* should investors have updated their prior beliefs that an OECD country could default on its sovereign debt? Even if we accept that the Greek experience was highly salient of what *could* happen to an OECD country that mismanages its public finance, it represents only one event (literally, the first ever) of the broader "rich country's default" class of events. With a statistical analogy, the Greek experience variable has a high coefficient (strong size effect), but also a high standard error (low statistical significance) due to a limited sample size. Plenty of empirical works in behavioral economics and finance have shown that actors tend to be insensitive to the basic notion that the same evidence from different sample sizes should give us a different confidence in the results (starting from Tversky and Kahneman 1974, Griffin and Tversky 1992, but many others TO BE CITED). As these studies have shown, the neglect of prior baseline probabilities and insensitivity to sample size lead agents to over-rely on representativenss in their decision making process. It should be noted that while the representativeness heuristic via neglect of baseline probability may be most relevant at the beginning of the crisis, its low sample size variant would explain the continued reliance on the group acronym for allocation purposes during later stages of the crisis.

A second heuristic originally suggested in Tversky and Kahneman (1974) is also relevant to explain the continued use of heuristics as the crisis unfolded, i.e. the availability heuristic. Simply put, human beings tend to assess the probability of an event by the easiness with which examples of its occurrence can be brought to mind, i.e. are available. Mutatis mutandis, the implication to our case is straightforward. As element A becomes more and more associated to group B, the easiness with which, and hence the likelihood that, actors will think of B when they are exposed to A increases. Since the remaining countries (alongside country A) are also members of B, actors will update their priors about the whole group, albeit to different degrees. To reiterate, the contention here is that, as the crisis unfolded, the sheer repetition of the acronym PIIGS in relation to the five countries increases the likelihood that actors would think of a default type group of countries once they are prompted to think of any individual member.

The theory sketched above, while novel in its application to sovereign entities, is consistent with well-known formal models constructed to explain stock market developments that are apparently at odds with the prediction of the EMH. For example, Griffin and Tversky (1992) construct and test a model to explain the pattern of under- and over-reaction [9]. In their framework, agents update their beliefs based on both the *strength* and the *weight* of the evidence. Strength refers to aspects of the evidence such as its salience and extremeness, while weight refers to its statistical informativeness. The latter is clearly related to the previous discussion of small sample bias underlying the representativeness heuristic. In particular, Griffin and Tversky (1992) show how people tend to focus too little on the weight of the evidence, and too much on its strength, thus violating Bayes' theorem. More specifically, under-reaction (conservatism) tends to arise when actors face evidence that has high weight but low strength. Unimpressed by the low salience of the evidence, actors react only mildly. By contrast, when the evidence is of the high strength/ low weight type, actors over-react in a manner consistent with representativeness. In both cases, the reaction is present - and in the right direction, given the evidence - but is either exaggerated or attenuated relative to that of a fully Bayesian actor. Moreover, such psychological sub-rational outcome is not minimized by expertise, experience, sophistication and, more generally, any of the traits associated with human capital. Indeed, experimental studies have found not only that such behavior is also present among experts - who we would otherwise expect to be better informed -, but that over-reaction is actually *more* likely among experts than novices as the overall uncertainty of an event increases (CIT NEEDED). As Griffin and Tversky (1992) succinctly summarize it: "If [...] the stock market cannot be predicted from present data, then experts who have rich models of the system in question are *more* likely to exhibit overconfidence than lay people who have a very limited understanding of these systems." (p. x, emphasis mine)

Building explicitly on these, Barberis et al. (2005) develop a model of the stock market where agents overreact to new information due to representativeness bias (and under-react due to conser-

[9] Technically, they are concerned with under and over-confidence more generally. Nevertheless, Barberis et al. (2005) - to be discussed shortly - show that it can be applied to under and over-reaction in financial markets more specifically

vatism bias)[10]. Once again, under the assumption that a consistent series of good (or bad) earning announcements represent high strength/low weight information, the model predicts over-reaction in the correct direction. The connection to the European sovereign bond crisis should be evident. At the start, developments in a given country (say, Greece) is surely highly salient, but should have relatively low informativeness about another country (say, Ireland), above all in a context where the prior baseline probability of an event (default) is low. Of course, as Griffin and Tversky (1992) aptly notice, the difficulty in testing these hypotheses is that, in practice, it is not always clear what the empirical equivalent of various combinations of strength and salience would look like. In the "Measurement strategy" section, I will delineate a simple procedure to select informational evidence that is relatively high (and varying) in strength and low (and fixed) in salience, thus allowing us to test the over-reaction part of the model.

To sum it up, I propose and test the following hypotheses:

- **Hypothesis 1**: An increase in sovereign bond risk premia[11] in a given Southern European country leads to an increase in the number of articles using the PIIGS heuristic in reference to the other members of the group.
- **Hypothesis 2**: An increase in the number of articles using the PIIGS heuristic in reference to some Southern European countries leads to an increase in sovereign bond risk premia in the other members of the group.

Moreover, while the countries under study share some similarities in terms of economic and political characteristics - hence why they were grouped together in the first place - the argument proposed here suggests that this acronym has also obfuscated systematic intra-group differences. As Gray 2013 has shown, the "company that states keep" matters differently depending on each member country's prior trustworthiness. In other words, lumping together "good" and "bad" country types will result in the

[10] I focus on Barberis et al. 2005 as they explicitly refer to represnetativeness. Also, I focus only on the over-reaction part of the model, as it is the most relevant to the present paper. See Daniel et al. (1998) for an alternative model of investor sentiment aiming at reconciling the empirical findings of under and over-reaction in financial markets.

[11] Please bear in mind that all the analysis is done on both 10 year sovereign bond yields and their spread from Germany's equivalent bonds. For simplicity, I word it as "risk premia", which should be interpreted as including both.

former's loss and the latter's gain in reputation. By definition, in the present context there is no "good" type; hence, it seems unlikely that any member of the group could have benefited from being associated to the rest. Nevertheless, it seems natural to expect Greece and, to a lesser extent, Italy to be the prototypical "bad" type in the groups[12].

To sum it up, the theoretical expectations generally apply to all countries in the group, although we also suggest the possibility of heterogeneous effects. As such, empirical analysis will focus on all countries pooled together as well as on each individual country separately. In line with the reasoning underlined above, in the single country case we would expect the Spain, Ireland (and one day POrtugal) to be the most affected by the peer effects, while the Greece and, to a lesser extend, Italy to be least affected. Whether this difference is in terms of size effects or statistical significance can hardly be theorized a priori.

5 Research Design

5.1 Measurement

Scholars working in finance and communication have usually employed one of two measurement strategies, which we could label as "general" and "targeted" (for a discussion of this distinction in a similar context see Büchel 2013). At times, authors have simply looked at the frequency with which the tokens of interest are used without differentiating between the target country and the other members of the group. For example, this was the approach in Brazys and Hardiman (2015) and Linsi and Schaffner (2019)' studies of PIIGS and BRIC acronyms, respectively. The weakness of this "general" approach is that it results in a mix of information about the target country and the other members, thus making it difficult, if not impossible, to distinguish between genuine "peer group" effects from standard informational effect of news media (i.e. the effect of articles about Spain on Spanish bonds). The second approach, more prominent among scholars investigating the impact of communication on

[12] The two clearly differed from the rest of the group in terms of public finance management as evidences by the public debt-to-GDP ratio prior to 2009.

financial markets more broadly, is to restrict the focus on the target entity (country, in this case) by imposing an explicit set of search criteria. For example, Büchel (2013) search for politicians' last names and at least one crisis-related key word (e.g. "Tsipras" and "crisis"). While it is obviously desirable to restrict news information to a specified and easily recognized entity, this approach also comes at a cost. In particular, while the "general" approach runs the risk of inadvertently incorporating information about the target country, the "targeted" strategy - at least as usually implemented - suffers from the opposite risk, i.e. that of incorporating information about the other countries. Clearly, while an article including the words "Tsipras" and "crisis" is *also* about Greece, it might not be *mostly* about Greece. The main focus of the article might be on Spain while Greece is only mentioned en passim. While the two approaches can be combined to assess the effect of both "targeted" and "general" news - e.g. Büchel (2013) -, this does not solve the underlying uncertainty about what is being excluded and/or included and, hence, measured.

Keeping the above discussion in mind, I propose an alternative simple strategy. Instead of searching for news articles about a specific country, I search for news articles on the Factiva (and LexisNexis as a robustness check. Results available upon request) database that are *not* about the target country. I do so by querying the following search string:

"PIIGS" and not("Country" or "Adjective" or "Population") [13]

This string greatly minimizes the possibility of measurement error. The articles retrieved are, by construction, *not* about the target country[14]. It should be noted that this is arguably the most conservative search criterion one could use, as it even excludes all articles that use the acronym PIIGS followed by the parenthetical "Portugal, Italy, Ireland, Greece, and Spain"[15]. While a country men-

[13] E.g. PIIGS and not(Greece or Greek or Greeks). Using PIIGS instead of PIGS also have a non trivial advantage: we don't have to worry about the news coverage of the pork market.

[14] One could imagine a situation where the country is solely described in terms of its capital. I randomly selected 100 articles for each target country and manually searched for the capital. In only one case (out of 400) my search string failed by including an article that mentioned Athens en passim

[15] Moreover, as noted before, the PIIGS acronym is a tough case to study the effects of heuristics also because its used was banned in some news media and institutions

tioned only in parenthesis would be unlikely to be the main topic of the article, this would cast doubt on the assumption that the news articles affect investors' perception of that country's creditworthiness only by *implicit* association with the other members via the PIIGS heuristics.

To relate this strategy to the previous theoretical discussion, the "NO country" search string guarantees a fixed low informativeness (weight) about the target country since it is never mentioned in the text. At the same time, this strategy allows for varying degrees of strength of the signal captured by the volume of articles using the acronym per unit of time. In other words, articles discussing and describing Spain/Italy/Portugal/Greece as a member of the PIIGS are likely to be salient to investors as they provide information about the Spanish/Italian/Portuguese/Greek political-economic situation. Nevertheless, since Ireland is never mentioned in the texts, the the articles should have low informativeness about the prospects of the Irish economy.[16]

To summarize, the proposed measurement strategy is novel and different from that used in other studies (e.g. Brazys and Hardiman 2015 or Linsi and Schaffner 2019) as it allows us to investigate the acronym's "peer effect" using sources that are by construction not directly related to the target country. This way, the empirical results can be interpreted as evidence that the target country is paying the price of being "guilty by association", so to speak. It also clearly differs from standard contagion studies looking at assets' correlations between the target country and the other group members (Brooks et al. 2015).

Figure 1 displays the end result of this process, i.e. the daily distribution of articles that mention the acronym PIIGS without mentioning the reference country from October 2009 to the end of 2015. To ease comparisons with previous studies, I also graph the number of articles containing the acronym PIIGS and that also mention the target country at least 2 times (the blue bars)[17][18]. Three points are worth noticing. First, as one would expect, the case of Greece is different from the rest as evidenced

[16] The underlying assumption is that the numbers of articles using the acronym PIIGS about a country is a function of the strength of the set of information being reported in the article. The assumption is justified in light of the empirical literature on media and economics. Indeed, one of the most robust findings is that economic developments affect the volume of news articles. See, for example, Liu 2014

[17] Searching for articles that mention the target country at least thrice results in similar graphs

[18] From now on, I will refer to "YES articles" to describe the the articles that contain the acronym as well as the target country and to "NO articles" for the articles that contain the acronym but do not contain any mention of the target country

by the higher number of articles mentioning the country (the blue bars) relative to the articles not mentioning it (red bars). Second, the histograms do have the familiar hump-shaped form that is visible in the 10-years interest spread of Southern European countries during the crisis (P.S.: one day the graph will have the spread overlaid on it). The last phase of the Greek sovereign bond crisis (Summer 2015) is an exception to this trend as there is no increase in the number of articles using the acronym. At that point, the crisis was confined to Greece and the remaining countries were on a path to recovery. Moreover, as mentioned before, the relative infrequency of its use might also be due to the fact that the acronym became less socially accepted over time. Third, while the two series clearly track each other, there is a great deal of variation. Indeed, the Pearson correlation coefficients for the two series is between a minimum of 0.24 for Greece to a maximum of 0.33 in the case of Italy.

Fig 1a: PIIGS acronym with and without reference to Greece

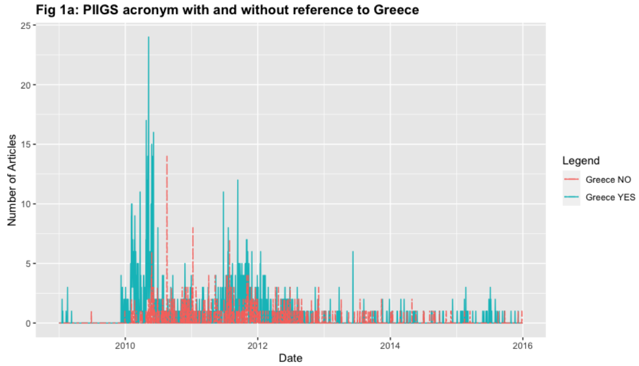
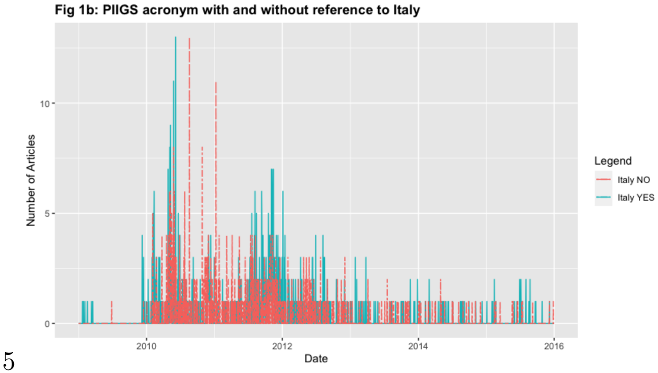


Fig 1b: PIIGS acronym with and without reference to Italy



.5

Fig 1c: PIIGS acronym with and without reference to Spain

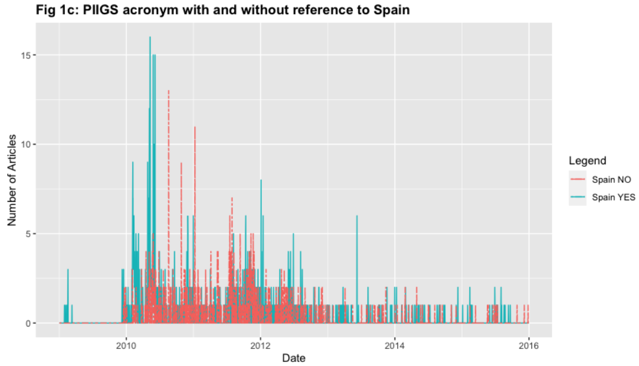
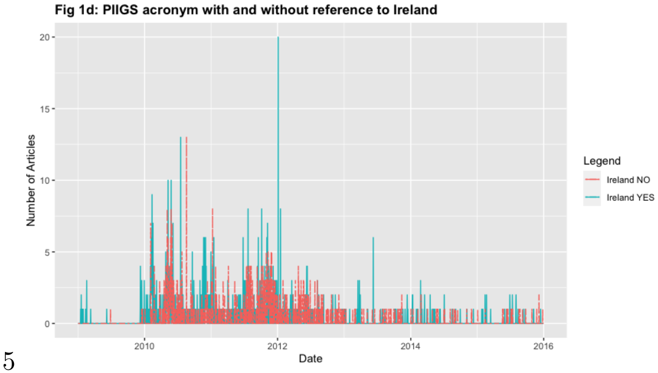


Fig 1d: PIIGS acronym with and without reference to Ireland



.5

5.2 Sample and Variables selections

5.2.1 The determinants of Sovereign Bond Spreads

The literature distinguishes between four potential determinants of sovereign bonds interest rates: exchange rate risk, liquidity risk, credit risk, and general risk aversion (D'Agostino and Ehrmann 2014). Clearly, **exchange rate** risk is less relevant in a monetary union (although the euro/dollar exchange rate is used as a regressor to control for EU-wide shocks). To control for liquidity risk, I include the overall outstanding amount of **public debt** (e.g. Gomez-Puig 2006)[19]. Likewise, I proxy for general risk aversion via the corporate bond yield spread in the US. In particular, I follow the standard convention in the literature and use the **spread between Moody's Seasoned Baa and Aaa Corporate bond yield** (Codogno et al. (2003); Liu 2014). As a second proxy, I use the **VIX**, a measure of global volatility risk premium (Longstaff et al. 2011). Some authors have suggested that the size the EU market justifies the use of regional (rather than global) risk aversion. As such, I use the EU-wide CPI index to proxy for regional market risk (Spyrou 2013)[20]. Finally, I include several macroeconomic variables to proxy for country-specific credit risk: **inflation rate**, **real GDP growth**, **unemployment rate**, **current account balance**, and **budget balance** (e.g. Beirne and Fratzscher 2013). Given the different time frequency of the variables, I follow the literature and use standard interpolation techniques (e.g. Hauner et al. 2010). In the main text, I (will) show results from carrying forward the previous observation. This choice is consistent with the assumption that economic agents update their information about a country's creditworthiness as soon as they information becomes available and they do so all at once. Of course, given the plethora of informational sources in today global finance, one may argue that economic agents rely on a more continuous stream of information. In the appendix, I show that the results remain unchanged if I use linear and spline interpolation for all variables at lower frequency.

[19] After I completed the analysis, I realized that a better proxy for liquidity risk is the bid-ask spread of the 10 years sovereign bond themselves. I will use it next time (Afonso et al., 2014)

[20] An alternative, that I have not explored so far, is to use the difference between the ECB reference rate and the 3 month Euribor. Quite frankly, though, I have yet to find a convincing explanation for why this should capture risk aversion rather than liquidity.

Moreover, as a robustness check, I also augment the model with a measure of central bank communication. In particular, I rely on the KOF measure of monetary policy, which translates ECB President's forward-looking statements on price stability into a quantitative index that contains information about the future course of monetary policy (De Haan 2008). The main reason to use the KOF measure - rather than a more standard measure of monetary policy - is that it allows for a clearer temporal ordering in the Cholesky decomposition. Indeed, consistent with its forward-looking nature, the KOF measure has been shown to anticipate interest rate movements by 2 months **?** while, at the same time, affecting expected and actual inflation similarly as the actual main refinancing rate (Neuenkirch 2013). This is particularly important when it comes to variable ordering for the Cholesky decomposition (more on this later).

Furthermore, all models using the daily dataset also include an exogenous dummy for **Friday** to account for the "Friday effect" detected in the finance literature (CIT NEEDED). Following the literature, articles published in the weekends are averaged and are assumed affect financial markets the following trading day (Büchel 2013).

Finally, we need to pay particular attention to including variables that proxy for common shocks and contagion effects. Indeed, as noted in Kaminsky and Reinhart (2000)'s classic study on financial contagion, true contagion "arises when common shocks and channels of potential interconnection are either not present or have been controlled for" (p. 146). There are several ways to go about it. Given that confidence in my empirical results rests on how well I control for other channels of contagion, I explore several of them.

First, I take the standard approach of controlling for the unweighted average of the price of sovereign risk in the other member of the group (after excluding the country of interest) (Edwards 1983, Beirne and Fratzscher 2013).

Second, we know that **credit ratings** are a likely source of contagion effects (Longstaff 2010). As such, I control for Credit Rating Agency's announcements for the other countries in the group (Longstaff 2010, Missio and Watzka 2011). I follow standard practice in the literature and turn the letter grades into a numerical score (1-25) (e.g. Aizenman et al. (2013)). To avoid over-parameterizing an already rich model[21], I implement Principal Components Analysis on the credit rating announcements of the other PIIGS country (after excluding the target country) and include the first principal component as an exogenous variable [22]. Following the literature, other countries' CRAs enter the system of equation exogenously (Brazys and Hardiman 2015).

Third, to account for more specific mechanisms of contagion I proxy the linkages between sovereign bond markets by economic distance measures (Claeys et al. 2012). Following the literature, there are two main channels of contagion transmission, i.e. trade and the finance/banking sector (Pentecost et al. 2019). To begin with, I weight interest rates by the target country's trade exposure to each other country's in the group (e.g. Greece's imports plus exports as a percentage of GDP towards Italy divided by overall exports and import towards Southern European economies) [23]. Likewise, sovereign contagion may happen via integrated banking systems. As banks diversify their holdings of sovereign debt to minimize the expected cost of individual country's default (ex ante diversification), this is likely to act as a contagion mechanism once a crisis starts (ex post contagion) (Muratori 2015). As such, I explore the possibility of contagion via the bank sector by weighting each country's 10 year bond interest rate by the consolidated claims on immediate borrower basis by the nationality of reporting banks as a proportion of total peripheral EU countries. claims on each country.[24] This is a commonly used measure of bank exposure (Gómez-Puig and Sosvilla-Rivero 2013).

Fourth, I summarize the information contained in the other countries' (first differenced) bond yields via PCA to capture any group-wide co-movement. Following the literature, the first PC is then included endogenously in the VAR system instead of the unweighted average of the remaining countries' interest rates (Altınbaş et al. 2021)[25]. The extracted financial shocks are commonly used to investigate and/or control for the presence and size of regional spillover effects in a VAR framework

[21] Moreover, it should be noticed that we are only interested in controlling for channels of transmission rather than estimating the contagion effect from one country to another. Hence, it seems sensible to try to summarize the information as much as possible)

[22] The first PC is deemed sufficient as it captures more than 80 per cent of variation in all cases

[23] This is done for the weekly and daily dataset. As trade exposure data starts only with the first quarter of 2010, there are not enough observations to use the weighted-by-trade contagion variable in the monthly dataset

[24] Except for Portugal since the BIS does not have systematic data on bank exposure

[25] As in (Altınbaş et al. 2021), the first PC explains around 80 per cent of variation

(Fukuda and Tanaka 2020, Altınbaş et al. 2021).

Finally[26], in the most conservative specification, I include both the first PC of credit rating announcements as an exogenous variable as well as the first PC of sovereign bond interest rates as endogenous. The exogeneity assumption between the contagion variable and the target country yields would be clearly at odds with the premises of the paper. Thus, that contagion variable - weighted or unweighted - always enters endogenously, although prior to the target country's yield (Claeys and Vašíček 2014. By contrast, credit rating announcements regarding different countries' creditworthiness are usually modeled as (cross-sectionally) independent of each other once sovereign bond spreads are included in the equation (Corbet 2014, Brazys and Hardiman 2015, Aizenman et al. 2013, Afonso and Martins 2012, Longstaff et al. 2011). As such, they enter the system of equation exogenously.

Finally, the main variables of interest are either the simple 10 year government bond yield or its spread from the equivalent German bond. As it is standard in the literature on EMU, I use the 10-year German government bonds as the benchmark yields. By subtracting it from each country's yields, common developments in monetary policy and inflation expectations are removed and the resulting variable captures the country-specific risk premium (Mosley 2003). Following Brazys and Hardiman 2015, I operationalize the interest rates variable in absolute value (i.e. absolute value of first difference). The rationale is that, while we know that articles containing the PIIGS acronym are overwhelmingly negative, it does not follow from the theory that the "peer effect" should be exclusive to negative news[27]. This way, we can also compare the results to that of Brazys and Hardiman 2015, the study that comes closest to the present paper. I run all models twice, although I will show the results for the spread variable only.

More finally, all models also include the number of articles that do mention both the acronym and the target country at least three times (the "YES articles"). Notwithstanding the weaknesses

[26] Another way, not explored yet, is to inlcude all countries' yields separately as exogenous variables as in Kolponen et al. (2012)

[27] This does not run against what previously argued in the theory section. While "peer effects" should not materialize *only* during crisis (see also Brooks et al. 2015), they are likely to be stronger during crises. The possibility of the effect being conditional on the state of the economy is not explored in this paper - I would like to do so in the next, on the BRICs.)

underlined above, this is important for at least two reasons. First of all, the literature on finance and text analysis has shown that the volume of articles can be a strong predictor of financial market developments (e.g. Liu 2014). Second, this allows us to block the "informational channel" of news articles. On a given day, we might have the same number of NO articles and YES articles (it indeed happens). Excluding the latter would inflate the coefficient of the former as it would not include part of its effect. As such, it is a particularly conservative strategy.[28]

5.3 Methodology

As briefly mentioned before, previous studies may suffer from model misspecification insofar as they do not account for the the possibility of reverse causality. For example, Linsi and Schaffner (2019) explicitly qualify their results against a causal interpretation on the ground that their single equation model (following Brooks et al. 2015) does not account for reverse relationships. As such, in this paper I model the heuristic peer effect in a system of equation. This is in line with numerous studies in the sovereign bond yields literature (e.g. Neri and Ropele 2015, Yang 2005) and also been a prominent tool in political science and political economy literature (Brazys and Hardiman 2015, Webb 2018)).

5.3.1 PanelVAR Panel Granger causality.

Since its introduction by Holtz-Eakin et al. (1988), panel VAR (pVAR) models have entered the toolkit of both economists and, to a lesser extent, political scientists (Galariotis et al. 2016, Tang 2008). Panel VAR is particularly well-suited for analyzing the transmission of shocks over time and across units (Canova and Ciccarelli 2013). In particular, a pVAR approach allows the researcher to model static and dynamic inter-dependencies as well as cross sectional heterogeneity. In essence, a pVAR is a combination of single equation dynamic panels and vector autoregression (Sigmund and Ferstl 2019).

Following Abrigo and Love (2016), consider a k-variate homogeneous pVAR of order p with panel-

[28] Incidentally, I will not show the results for YES but they are pretty interesting. and somehow counter intuitive. It is very often the case that YES articles do not have an effect while NO articles do!

specific fixed effects represented by the following system of linear equations (deterministic variables are suppressed for ease of notation):

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + ... + Y_{it-p+1}A_{p-1} + Y_{it-p}A_p + X_{it}B + u_i + e_{it} \tag{1}$$

Where $i \in [1, 2, ..., N]$, $t \in [1, 2, ..., T]$, Y_{it} is the vector of endogenous variables (1 x k), X_{it} is a (1 x l) vector of (possible) exogenous variables, and u_i and e_{it} are (1 x k) vectors of panel fixed effects and idiosyncratic errors, respectively. The A_1, A_2, ..., A_{p-1}, A_p and the matrix B are parameters to be estimated. The innovations e_{it} are assumed to be stationary around zero, independent and normally distributed. While cross sectional units are assumed to share the same data generating process (i.e. the A and B matrix are common to all sections), the introduction of unit fixed effects accounts for systematic cross-sectional heterogeneity. As it is the case with standard panel data models, the parameters can be estimated jointly with the fixed effects or after removing the unit specific effects. With the presence of lagged dependent variables by construction the usual concerns about Nickell's bias apply (Nickell 1981), although the bias diminishes as the time dimension increases. To avoid bias in the estimates, various estimators based on Generalized Method of Moment (GMM) framework have been proposed. One possibility is to estimate the variable in first difference (FD) by instrumenting lagged differences with levels and/or differences from previous periods (Anderson and Hsiao 1982). Alternatively, one can subtract the average of all available future observations instead of using deviations from past realizations. This way, past realizations remain valid instruments as they are not included in the transformation. The forward orthogonal deviation (FOD) approach, first proposed by Arellano and Bover 1995, is more efficient, although the differences diminish as the time dimension increases. While these estimators were originally designed for "small T, big N" datasets - i.e. those situations where Nickel's bias is most severe - they have been shown to behave well even as the time dimension increases (Judson and Owen 1999, Alvarez and Arellano 2003) and are routinely used in applied research. As it is the case in standard VAR, the moment conditions become irrelevant when unit roots are present. As such, integrated variables need to be transformed to ensure stationarity. As such, I test the univariate properties of variables using panel unit root tests (see Appendix, eventually) and first difference those that contain a unit root. I then rerun the test on the first-differenced variable to make sure that it is stationary.

From the reduced-form pVAR models it is also possible to test for Granger non causality. Panel Granger causality is a common methodological tool in the sovereign bond economic literature (Gómez-Puig and Sosvilla-Rivero 2013) as well as in the broader political science literature (Hood et al. 2008). Moreover, notwithstanding its well-known weaknesses (e.g. Kilian and Lütkepohl 2017), such approach is particularly well suited for the hypotheses under study as it provides a convenient way to formally tests the informational content in a system of equation. The central notion underlying Granger causality is one of predictability. In particular, one variable Granger causes another if, given an information set, past information about the former improve the forecast of the latter beyond its own past information (and that of other variables, in the multivariate case) (Gómez-Puig and Sosvilla-Rivero 2013). As such, via Granger causality we can test if the number of articles containing the acronym PIIGS (but do not mention the target country explicitly) contain useful information to predict the target country's government bond yields beyond its past history and the past history of other variables. While a number of Grenger (non)-causality tests have been proposed in the pVAR literature, I choose the one recently proposed by Juodis et al. (2021) for two reasons. First of all, unlike the GC test proposed by Holtz-Eakin et al. 1988, it is not restricted to homogeneous panels and "large N, small T" situations. Second, unlike that of Dumitrescu and Hurlin 2012, it allows for the inclusion of other covariates. As a robustness check, I also use the Granger causality test by Dumitrescu and Hurlin 2012 on the bivariate relationship between sovereign bond spreads and the PIIGS variable.

Clearly, the use of panel VAR and Granger causality entails advantages as well as disadvantages (Hood et al. 2008, Canova and Ciccarelli 2013). On the one side, pooling all observations together results in remarkable efficiency gains. On the other side, it imposes the dubious assumption of causal homogeneity. Indeed, as underlined in the theory section on the differences between source and target countries, there are good reasons to expect some scope condition for the hypothesis. As such, I now turn to single-country models.

5.3.2 BVAR and Granger causality.

As the concept of Granger causality in individual time series has been well known to political scientists for some time, and its description is a simplified version of the Granger Causality tests for panel dataset, I do not further elaborate on it. For an introduction from a political scientist see Freeman (1983). By contrast, I will spend some time explaining the VAR methodology as it differs from the previous discussion insofar as I use Bayesian estimation methods[29]. The rationale for relying on Bayesian estimation is two-fold. First of all, it helps avoiding over-parameterization of an already rich model (as it is in our case) while avoiding the known pitfall of classical estimation, such as over-fit and overestimation of coefficients of distant lags (Brandt and Freeman 2006). Second, Bayesian estimation allows for alternative identification schemes beyond the Cholesky decomposition (more on this later). More generally, it is often suggested as a valuable option for problems where model scale, endogeneity, persistence, and specification uncertainty are all present at the same time as it subsumes more familiar models (such as frequentist VAR) and allows for sounder statistical inference (Sattler et al. 2008) I will completely skip the technical explanation of the estimation, the choice of the priors and hyper-parameters for now. In a nutshell, I follow Giannone et al. 2015 and treat prior informativeness in the spirit of hierarchical models. In other words, the priors are treated as additional parameters to be estimated, which they receive their own priors (hyper-priors) with hyper-parameters. The hyper-priors are a combination of three widely used priors in the literature: the Minnesota (Litterman) prior, the sum-of-coefficient prior, and the single unit-root prior.

[29]I have run the models also with highly uninformative priors - the approximate equivalent of frequentist VAR - but I will not show them here to save space for the new analysis. The results are substantively the same

5.3.3 Diagnostic tests

The usual diagnostic tests were performed in both panel and standard VAR[30]. [31] As it is well known, VAR-based structural analysis can be carried out only if the VAR model is stable, i.e. if all moduli of the companion matrix are less than one, thus insuring that the panel VAR is invertible and has a infinite-order vector moving-average representation (Lütkepohl (2005)). As such, I run the stability condition diagnostic test and verify that the system is not explosive. Moreover, as mentioned above, I test for serial correlation in the reduce form residuals and augment the lag length until they show white noise behavior. In most models, residuals appeared to be non normally distributed. As such, the confidence intervals are constructed using bootstrap resampling methods. Finally, regarding the Bayesian models, I use the Geweke statistics to assess MCMC convergence.

5.3.4 Identification strategies

While the simple Impulse Response Functions (IRF) can be estimated by rewriting the model as an infinite Vector Moving Average (VMA) (provided that the system is invertible), these IRFs do not have a structural interpretation due to the contemporaneous cross-correlation between innovations (the residuals in each equation). In practice, one has to impose further restrictions in order to proceed with a structural interpretation (Lütkepohl (2005)). Several identification strategies are available, each with its own strength and weaknesses. To increase our confidence in the results, I rely on three widely employed identification strategies.

5.3.4.1 Cholesky decomposition

Posing a recursive structure to the contemporaneous relationship via Cholesky decomposition is arguably the most common approach to structural analysis in a VAR framework. In a nutshell, it amounts to ordering the variables from the most exogenous to the least exogenous. The variables

[30] I do not literally run all diagnostic for all models - at the end of the day they are hundreds. I do so for the main models. For example, I do not rerun all the tests for each single change in the ordering of the variables in the Cholesky decomposition.

[31] Since the pVAR model is interpreted only via the Cholesky decomposition (thus resulting in a just-identified model), the Hansen's J statistic of overidentifying restriction is not reported.

ordered first can affect all the subsequent variables contemporaneously, but can be affected by the other variables only with a lag.

A useful first step to decide on the order of contemporaneous relationship is to divide the variables in three blocks (Galariotis et al. 2016). First, the global (or regional) variables (e.g. the VIX); second the domestic variables (e.g. GDP growth); finally, financial market variables of interest (in our case, the sovereign bond interest rate and the count of PIIGS articles). This broad first-level ordering is widely accepted in the literature as it is assumed that financial markets react quickly to changes in the real economy at both domestic and global level, while changes in the domestic economy react with a lag to changes in the global (or regional) economy[32]. What is more contentious, though, is the specific ordering within the blocks (e.g. should one impose a contemporaneous restriction of unemployment shocks on inflation or the other way around?). Ordering the major variables of interest (NO articles) last is the most conservative approach (as it eases concerns about contemporaneous reverse causality from sovereign bonds to PIIGS) and is standard practice in the literature.

The baseline specification (all figures in the main text will come from this) has the following ordering (parenthesis indicates the three blocks):

(VIX, ER) (i, GDP, u, cab, debt, deficit) rating KOF (contagion, target spread, NO, and YES articles) [33]

The VIX measure is the most exogenous one as it is the only global variable, followed by the dollar/euro exchange rate. This implies that global uncertainty in financial markets affects all variables contemporaneously, but is affected only with a lag. Likewise, the exchange rate variable affects all variables contemporaneously except for global financial market uncertainty. The ordering within the second bloc is complicated by the presence of multiple variables. I follow Afonso and Martins 2012 and order inflation first, followed by GDP growth, the fiscal variables (debt-to-gdp and deficit), and

[32]This holds as long as the country under study are not economically big enough (e.g. the US) to influence global variables instantaneously.

[33]Complete names: VIX, ER, inflation, GDP growth, unemployment, current account balance, debt-to-GDP, deficit, credit rating of target country, monetary policy indicator, contagion variables (e.g. unweighted average of other PIIGS' spread), target country's spread, NO articles and YES articles

the financial variables. Among strictly economic variables, the financial variables (contagion and target country's spread) are ordered last, which means that they can be affected contemporaneously by all other economic variables but cannot affect them contemporaneously. This is consistent with the idea that financial markets react quickly to policy developments. In other words, financial stress is a reaction to shocks originated in the real sector (Apostolakis and Papadopoulos 2019). Fiscal variables are placed in the previous position so that they cannot have a contemporaneous effect on macroeconomic factors - due to policy lags - while output and inflation shocks are allowed to impact fiscal variables immediately due to the presence of automatic stabilizers. Then, I follow Neri and Ropele (2015) and order the remaining macroeconomic indicators (unemployment and cab), prior to the fiscal and financial variables, but after GDP growth. This is consistent with the idea that GDP growth affects unemployment and the current account balance immediately, while the feedback loop takes place only with a lag[34]

At the same time, we assume that the contemporaneous relationship between financial markets and the media goes from the former to the latter. This is assumption is consistent with most studies on political communication and financial markets (e.g. Vliegenthart and Mena Montes 2014). The contagion variables is allowed to affect the target country's immediately, while it is affected only with a lag to capture the intuition that the developments in four fixed-security markets combined is more likely to affect the remaining market than the other way around, at least contemporaneously. This is consistent with typical studies on contagion effects (CIT NEEDED). The same logic suggests to order the NO articles (i.e. the articles about the remaining four countries) prior to the YES articles.

In between the second and third bloc, I place the country's credit rating as well as the monetary policy indicator[35]. The rationale is that it may react immediately to shocks to inflation, aggregate output, and the fiscal variables but, due to the well-understood monetary policy lags, will not affect

[34]Notice that the frequency of the measure can also helps with the ordering: given that unemployment is measured at a monthly frequency and GDP growth at a quarterly frequency, it is more sensible not to allow the former to contemporaneously affect the latter as this would be unlikely to be detected in the data anyway.

[35]It is not in the block because 1) Its order does not change and 2) The KOF indicator is used only as robustness check

any of those variables contemporaneously.[36]. Notice that the ordering of the monetary policy indicator is facilitated by the use of the KOF rather than a more standard measure of monetary policy. The forward-looking properties of the KOF indicator (see De Haan 2008) allow us to include this measure of (implicit) monetary policy in between macroeconomic domestic factors (second block) and the main variables of interest (third bloc). In other words, central bank's communication about monetary policy is allowed to affect financial markets and the media immediately - which is consistent with a vast number of studies about ECB communication (CIT NEEDED) - while it affects the real economy only subsequently, i.e. once the announced monetary policy is adopted. Likewise, changes in the country's credit rating are expected to affect financial and media variables immediately, but the real economy only with a lag. To decide on the order between KOF and changes in a country's credit rating, I rely on the different time frequencies. Being a discrete and slowly changing measure, the country's credit rating is order first, meaning that it cannot be affected immediately by the KOF measure.

It is well-known that, while unique, the Cholesky decomposition depends on the ordering of the variables, thus making any structural interpretation conditional on the "correct" recursive structure (Kilian and Lütkepohl 2017). As Antonakakis and Vergos (2013), it is particularly hard to justify any particular ordering of the variables on government bond yields. Indeed, some of the contemporaneous restrictions underlined above are debatable. For example, GDP growth is ordered prior to debt-to-GDP and deficit as percentage of GPD on the ground that automatic stabilizers immediately change the ration. Nevertheless, there is no consensus among macroeconomists on this ordering. Among others, Bouvet et al. (2013) argue in favor of the reverse ordering on the ground that government budgets respond only sluggishly to aggregate outcomes growth. Worse still, in other cases there is no clear guidance in the literature. For example, while the VIX is usually ordered first, it is not exactly clear why it should immediately affect, but should not be immediately affected by, the euro/dollar exchange rate. Of course, the same case applies to the ordering of the media variables. It seems

[36] Following the literature, this ordering is deemed appropriate even in the case of a monetary union where fiscal and monetary authorities are at different levels. For an application on Germany and the US, see Afonso and Martins 2012)

sensible to suggest that the way the media discuss all but one country in a given group is more likely to have an immediate effect on the way the remaining country is talked about rather than the other way. Nevertheless, as the crisis mostly originated in one country (Greece) and then spread to the rest of the group, such assumption is debatable.

Since testing for all possible ordering combinations would be unwieldy (as in, there are 13! = 6227020800 possible combinations), I employ the following strategy. I keep the three blocks (global/regional, domestic, financial and PIIGS) fixed and test for different combinations within each block. As such, I test for $n!_{bloc1} + n!_{bloc2} + n!_{bloc3}$ combinations. I report the results for the preferred specification in the main text and (will report) those for the alternative ordering in the appendix[37].

5.3.4.2 Sign restrictions

The inconsistency of short-term zero restriction with many economic models has pushed researchers to look for alternative identification schemes. A valuable alternative to zero restrictions and recursive identification is that of sign restrictions. Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005) show that structural inference in VAR models can be based on prior beliefs about the signs of the impact of certain shocks.

Importantly, sign restrictions can be derived more easily from theory as it often less controversial to claim that a given a variable has a positive (or negative) effect on another rather than it has no effect. They impose relatively weak prior beliefs on the structural responses - ”x does not increase y for t periods” -, thus making the identification strategy more credible (Danne 2015). Moreover, under certain conditions, it is possible to impose weak inequalities, thus subsuming the short-run zero restrictions (Kilian and Lütkepohl 2017)[38]. For this reason, such a strategy has become more and more common in the broad macroeconomic-finance literature (e.g. Beaudry et al. 2011).

[37] To be clear, I start from the main specification and change the ordering in the first block; then, again starting from the main specification, I change the ordering of the second block; etc. I also include only deficit (and not debt-to-GDP) as a fiscal variable. Including both would result in 720 combinations only for the second bloc. While I prefer keeping both in the main specification, the use of only one of the two fiscal variables is consistent with previous work as well (CIT NEEDED). The same logic will apply to the specifications for the sign restriction identification (I will discuss it explicitly in the main text later). Thus, I have 2! + 5! + 2! + 4! = 148 different combinations

[38] Nevertheless, standard solution algorithms are available for strict ineuqlities only. It is also possible to impose long-run weak inequalities and to combine weak and zero restrictions. These options are not explored in this paper.

As briefly mentioned before, one of the reasons I gave for shifting to Bayesian estimation is that it allows for alternative identification schemes. Indeed, sign restrictions are, for the most part, well defined only in a Bayesian framework (Moon and Schorfheide 2012). The advantages mentioned above come at a cost, though. Indeed, one key difference from recursive identification is that the structural parameters are no longer point-identified, but only set-identified, i.e. the parameters of interest can only be bounded (Kilian and Lütkepohl 2017). Another disadvantage is that it is not possible to identify multiple shocks at a time. This is often seen as a problem in macroeconomic studies that aim at identifying general equilibrium patterns characterized by multiple shocks and feedback loops (e.g. news shock, technology shock, demand shock, supply shock). Clearly, the goal here is more modest as I am interested only in one or two shocks (the NO articles shock and the spread change shock).

Description of the algorithm: Not done yet.

Following Uhlig 2005[39], I focus only on the responses to the shock of interest. Thus, all columns satisfying the theoretical sign pattern are considered admissible solution of the structural model (Kilian and Lütkepohl 2017). Given that one can estimate only one shock at a time, I focus on the shock to the NO article variable (hypothesis 2), the most original part of the analysis. Clearly, the sign restrictions cannot be inferred from the data, and need to be set on theoretical ground. I take advantage of the fact that the PIIGS acronym has been used during the crisis with a unequivocally negative connotation. Consistent with the interpretation of the shock suggested in the next section, I suggest that an increase in the NO article variable (a positive shock) is indicative of *future negative* expectations about the economy of the other members of the group[40]. In other words, it may affect the economic variables in the system only in a negative way (i.e. it cannot lead to positive investors' confidence).

The table below shows the sign restrictions pattern for all the variables in the model. Following the logic stated above, all the signs represent a deterioration of economic condition (e.g. unemployment has a plus sign meaning that negative expectations about the future economy in Southern European

[39] But see Kilian and Lütkepohl 2017, Ch. 13 for a critique

[40] Of course, given my measurement strategy, I cannot identify *which* member specifically.

countries cannot decrease unemployment). Similarly, I restrict the sign of the effect of a NO article shock to itself as well as to the YES articles variable to be positive (i.e. while a mouthful, this implies that negative expectations about a country's future cannot directly cause future positive expectations about that country's future). Whether the pattern holds also for the main variable of interest - spread - is obviously left for the data to reveal. Hence, there is no sign restriction in the table.

Unfortunately, though, attempting to estimate the full model results in estimation problems due to convergence issues. For practical reasons, then, I have to narrow the model. I elect to exclude the dollar/euro exchange rate on the grounds that general risk aversion is already partly accounted for by other variables (e.g. VIX). I also exclude the inflation rate as inflation was not a major concern during the period under study (and the differences across EU countries are negligible). Finally, following Mosley 2003, I use only one fiscal variable at a time (debt-to-GDP and deficit) on the ground that they capture similar elements[41]. I will show the results using the deficit variable as we know that investors are usually more concerned with the flow rather than the stock of public debt (CIT that 2013 short paper on Economic Letters).

Table 1: Sign Restrictions for NO Article Shock

Shock	VIX	i	GDP	u	Cab	Defic.	CRA	Contag.	Spread	NO	YES
NO	+	+	-	+	-	+	-	+		+	+

5.3.4.3 Substantive Shock Interpretation

As Kilian and Lütkepohl (2017) notice, statistical identification is a necessary but not sufficient condition for economically substantive identification. While orthogonalization allows to derive a shock that is exogenous to the rest of the system - stripped away by construction of the effects of the endogenous variables and of the remaining contemporaneous shocks -, it behooves the researcher to spell out the specific interpretation of the shock of interest. In our case, the shock to the NO article variable can be interpreted as news about expectations concerning future developments in peripheral EMU countries (minus the target country) and/or news reporting bias (the portion of news reporting about the

[41] Mosley (2003) also adds the two and uses a composite index for fiscal position.

countries that is not explained by changes in the observable)[42]. This interpretation is similar to that of most recent works on media and finance in a VAR framework (Gambetti et al. 2021). In particular, as mentioned above, an increase in its usage is a signal of negative expectations.

6 Results

6.1 pVAR

To briefly recap, our strategy to test for media-related peer effects is based on the following steps. First, we eliminate the common risk free rate by subtracting the German bond yield from each country's yields (Mosley 2003). Second, we augment a typical VAR model to study the determinants of sovereign bond interests rates by adding several measures of financial contagion (e.g. unweighted and weighted averages of the other countries' yields). The rationale is to control for as much variation as possible via standard channels of transmission. Finally, I include the YES and NO article variables. The former should capture the informational content specific to the target country. Once stripped away of all these factors, the NO variable is left to explain how the discursive reference to member countries as a cohesive "bad" type group leads investors to infer future developments about a country from present economic and political conditions in some other member of the group.

Table 1 shows the panel Granger Causality results for the bivariate as well as multivariate relationship between a country's spread and the NO articles variable in the monthly dataset. As the tables in the appendix show, using the weekly or daily dataset does not change the substantive results. Notice that I show the p-values for each lag instead that for the combined test (recall that the joint test is that all coefficient lags are jointly zero; hence, one being non zero would result in a statistically significant coefficient anyway). Notice also that the lag length can differ in the two equations because - after setting the maximum length as described below the table - the algorithm chooses the optimal one. By and large, both hypotheses are confirmed in this preliminary analysis. In both bivariate and

[42]For a review of the determinants of media bias see Gentzkow et al. (2015)

multivariate case, each variable contains information that helps predicting the other variable beyond its own lags (and those of the other variables in the multivariate case).

Table 2: Granger Causality in Monthly Panel Dataset

Direction of the Relationship	Controls	P-values
NO $\Rightarrow$ Spread from Germany		0.420 (t-1)
		0.000 (t-2)
	✓	**0.000 (t-1)**
	✓	0.314 (t-2)
	✓	**0.000 (t-3)**
Spread from Germany $\Rightarrow$ NO		**0.000 (t-1)**
	✓	**0.000 (t-1)**
	✓	0.436 (t-2)
	✓	**0.000 (t-3)**

Notes: The optimal lag length is determined independently in each equation by minimizing the Bayesian Information Criterion. The maximum length is set to 3 (one quarter) for the monthly dataset. All control variables - exogenous and endogenous - are included.All models allow for cross-sectional heteroskedasticity.

Turning to structural analysis, the Fig. 1-2-3 show the orthogonalized (via Cholesky decomposition) impulse response functions for the monthly, weekly, and daily datasets, respectively. The figures on the left show the effect of a one standard deviation increase in the number of NO articles on the country's spread. In all three cases, the figures show a statistically significant positive effect. In the first case, the target country pays an extra premium of around 10 basis point, which lasts only for one month (all figures start from zero as, by construction, the NO article variable cannot affect spread contemporaneously). Somehow surprisingly, the second figure shows a longer lasting effect. The third figure on the left seems to offer the most sensible picture of the relationship. It shows a high statistically significant effect fading away in 3 days. [43] Moving on to the discussion of the second hypothesis, the three figures on the right column show the effect of a one standard deviation increase in a country's spread on the number of articles containing the acronym PIIGS in reference to the other countries in the group. Recall that, in this case, the contemporaneous relationship is not restricted to zero, hence the response function does not need to start from the origin. Hypothesis 2

[43] These figures are highly representative of all the other IRFs that I have computed as robustness checks - not shown (yet). Once again, the only exception is the weekly dataset, which at times results in improbably response functions (always in the right direction but at times lasting too long to be believable).

seems also confirmed in the panel estimation: the target country experiences a 0.04 point increase in risk premium, which completely returns to its long run mean in the third month. Nevertheless, this is not a particularly impressive substantive effect: the mean of the NO article variable for the monthly dataset is 0.33. A similar story comes from the weekly and daily dataset. In the first case, a 0.05 point increase (the mean for the entire period is 0.29) which lasts until the 6th week. In the second case, we have an immediate positive effect that disappears after two days (the average of NO articles is 0.29 also in this case).

Figure 1: OIRF from pVAR Monthly

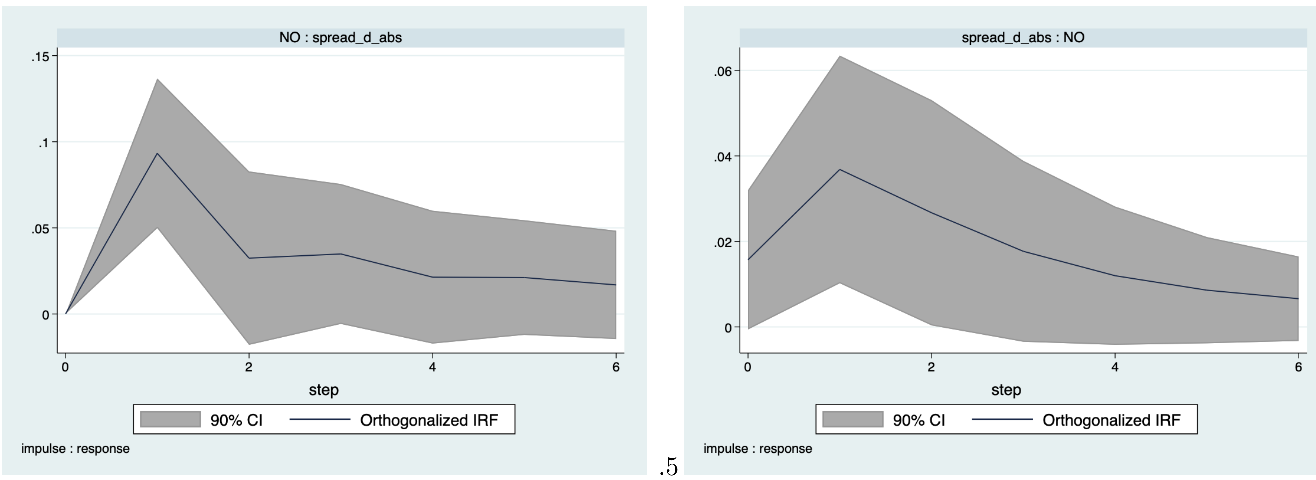


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Figure 2: OIRF from pVAR Weekly

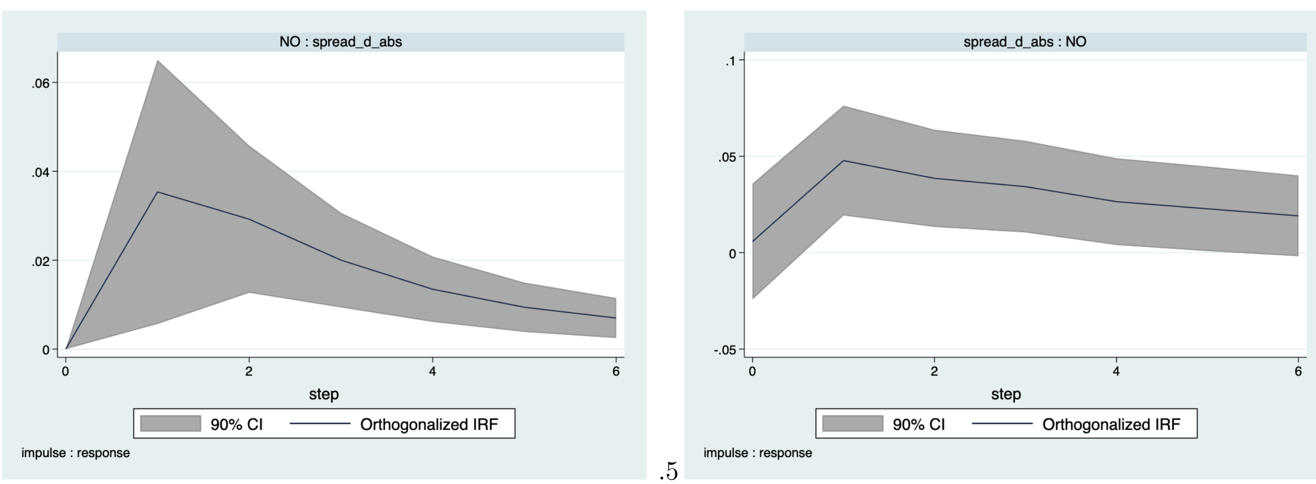

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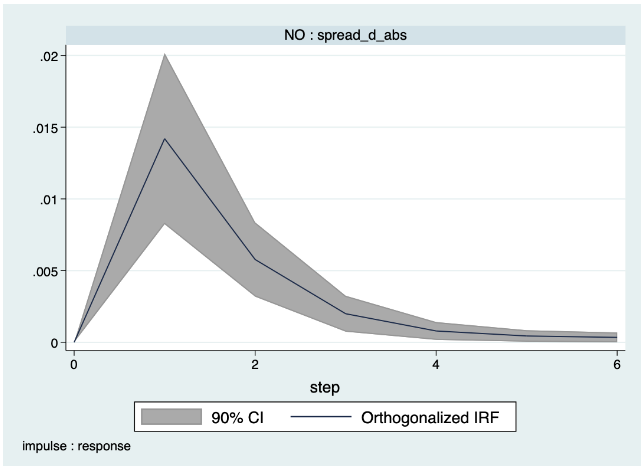
Figure 3: OIRF from pVAR Daily



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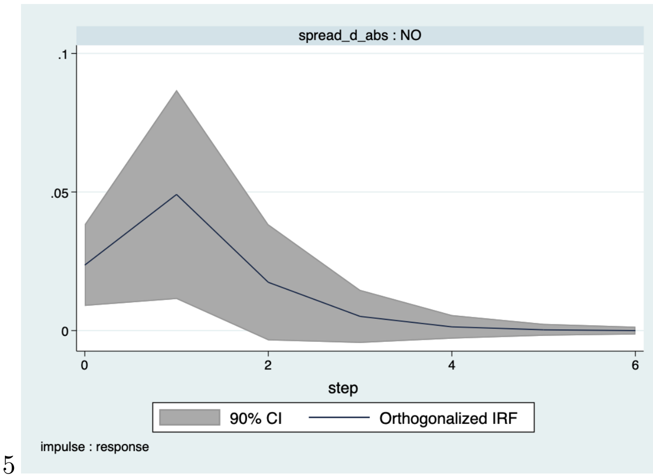


Next, I move to the country-by-country analysis. First of all, I test for Granger causality in the reduced form system for each country and dataset. The table below shows once again that Spain, Italy, and Ireland are distinct from Greece, whose spread is never Granger caused by the NO variable. Interestingly, though, except for the monthly dataset, the Greek spread does not Granger-cause the number of NO articles either. This is probably explained by the fact that all the increases in the Greek spread in 2015 took place in a no-contagion environment.

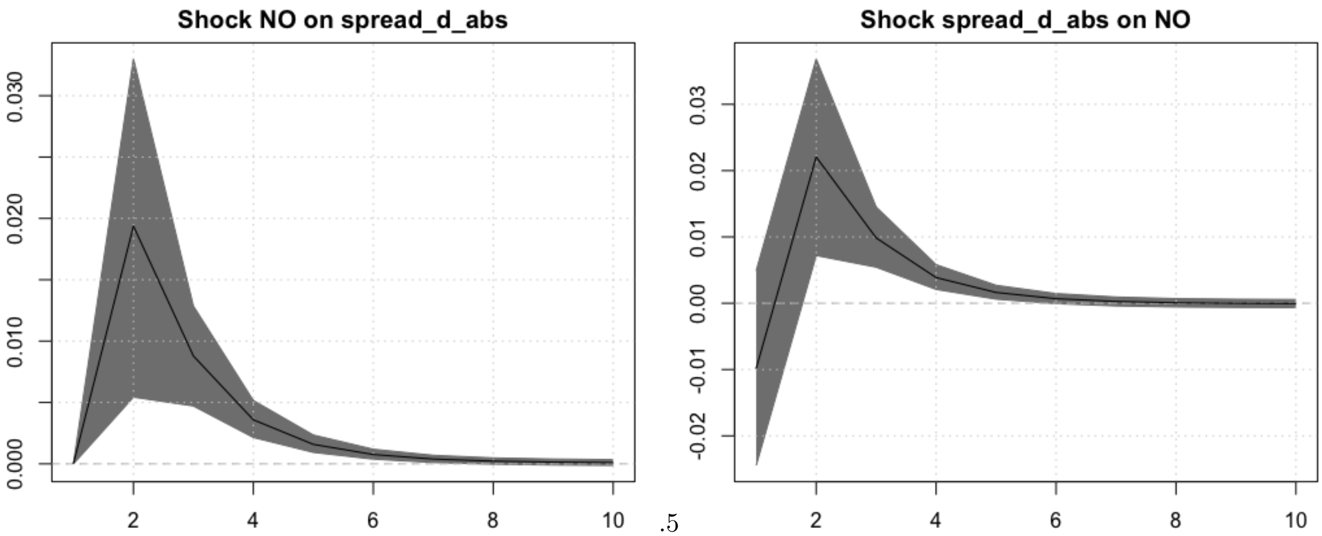
Table 3: Granger Causality in Weekly Panel Dataset

Country (time frequency)	Relationship	P-values
Greece (Monthly)	Spread $\Rightarrow$ NO	0.000
Greece (Monthly)	NO $\Rightarrow$ Spread	Not significant
Greece (Weekly)	Spread $\Rightarrow$ NO	Not significant
Greece (Weekly)	NO $\Rightarrow$ Spread	Not significant
Greece (Daily)	Spread $\Rightarrow$ NO	Not significant
Greece (Daily)	NO $\Rightarrow$ Spread	Not significant
Italy (Monthly)	Spread $\Rightarrow$ NO	Not significant
Italy (Monthly)	NO $\Rightarrow$ Spread	0.035
Italy (Weekly)	Spread $\Rightarrow$ NO	0.018
Italy (Weekly)	NO $\Rightarrow$ Spread	0.000
Italy (Daily)	Spread $\Rightarrow$ NO	0.000
Italy (Daily)	NO $\Rightarrow$ Spread	0.000
Spain (Monthly)	Spread $\Rightarrow$ NO	Not significant
Spain (Monthly)	NO $\Rightarrow$ Spread	0.000
Spain (Weekly)	Spread $\Rightarrow$ NO	0.078
Spain (Weekly)	NO $\Rightarrow$ Spread	0.000
Spain (Daily)	Spread $\Rightarrow$ NO	0.000
Spain (Daily)	NO $\Rightarrow$ Spread	0.000
Ireland (Monthly)	Spread $\Rightarrow$ NO	Not significant
Ireland (Monthly)	NO $\Rightarrow$ Spread	0.006
Ireland (Weekly)	Spread $\Rightarrow$ NO	0.000
Ireland (Weekly)	NO $\Rightarrow$ Spread	0.000
Ireland (Daily)	Spread $\Rightarrow$ NO	0.000
Ireland (Daily)	NO $\Rightarrow$ Spread	0.000

Notes: The optimal lag length is determined independently in each equation by minimizing the Information Criteria. As the criteria often suggest different numbers of lags I choose the one that is favored by most criteria. Most of the time it is one lag. The exception is the "spread to NO" equation for Spain in the monthly dataset. In that case, half of the information criteria suggest 1 lag and half suggest 3 lags. Using 3 lags would result in a p-value = 0.000.

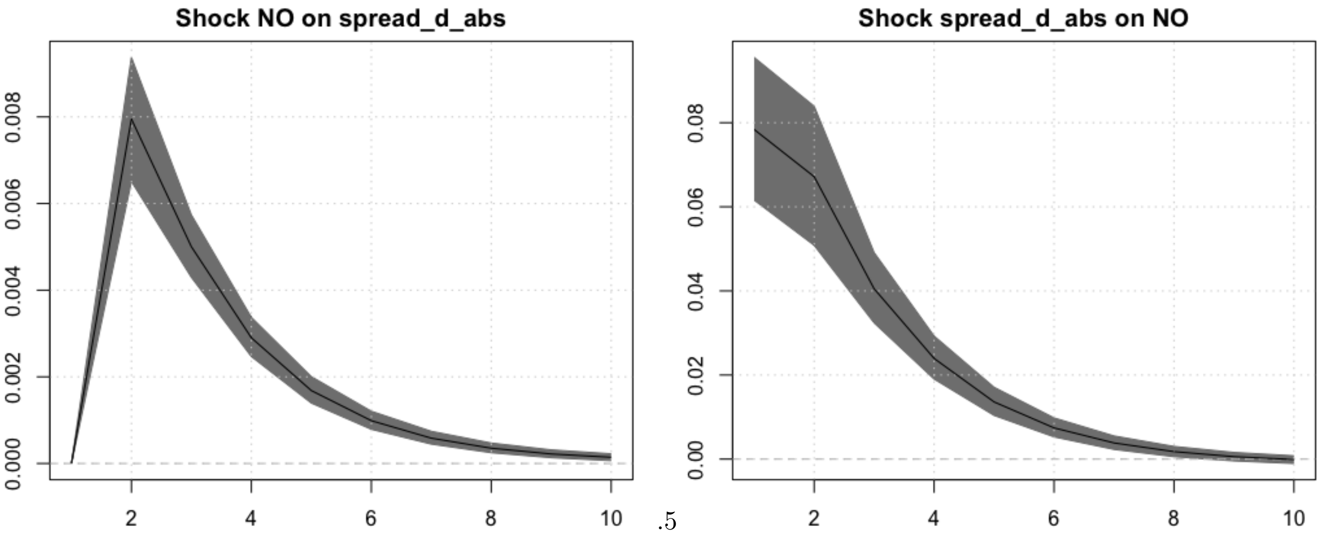
Moving on to structural analysis, I follow the literature on BVAR and show the 68 percent credible intervals for the IRFs (I realize I need to cite work and explain why 68, but it very standard in Bayesian VAR.). Once again, identification is achieved via Cholesky decomposition. I will show the results from the daily dataset only (monthly and weekly in the appendix). Fig. 4 shows the result for Greece. In both cases, we see a positive and statistically significant effect of a one standard deviation shock. It lasts approximately 5 days. In both cases, the effect is small (it peaks at 0.02 and then declines) but not that small after all. The Greek average for daily changes in spread is 23 basis point. The daily mean for the PIIGS articles that do not contain reference to Greece is 0.24.

Figure 4: OIRF from BVAR Daily (Greece)



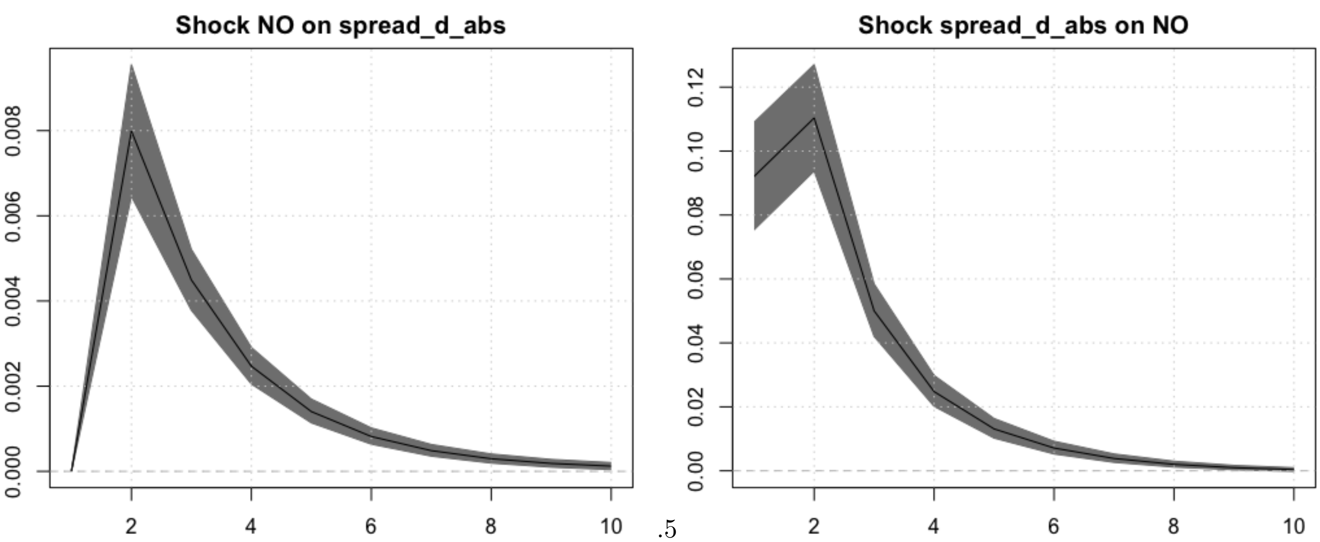
Likewise, Fig. 5 shows the same for Italy. The response functions are more precisely estimated. An interesting pattern emerges. The effect of the NO articles shock is long lasting (it fades away completely after 10 days) and its substantive effect is not even that small (somehow at odds with my expectations). The average daily change in spread is 5.8 basis point, and one SD increase in NO article increases the spread imperceptibly after one day, but then almost by 1 basis point after two days (more or less 15 percent of the overall daily change in Italian spreads). Moreover, Italy does look like a very meaningful source of contagion. With an average of 0.31 NO articles per day for the whole period, a one SD shock to the Italian spread leads to an immediate 0.08 unit increase in the number of articles using the acronym in reference to the rest of the group.

Figure 5: OIRF from BVAR Daily (Italy)



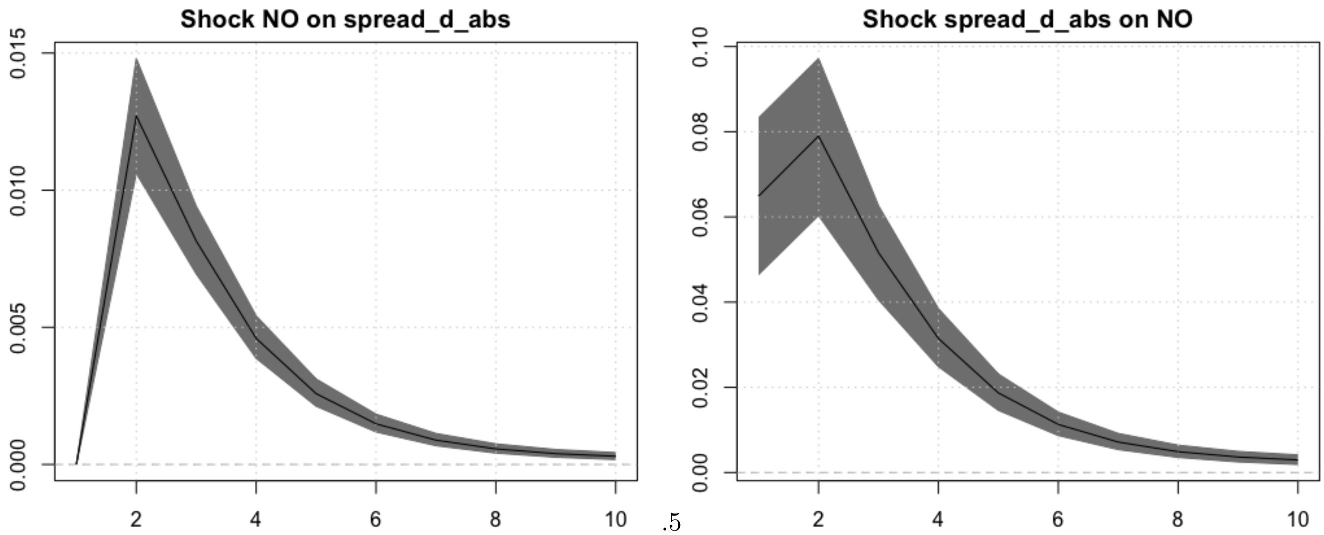
Pretty much the same picture emerges from the IRF for Spain (Fig. 6). The average daily change of Spanish spread is 6.2 basis points and the shock to the NO articles leads to a 0.8 basis point increase. The effect of a spread shock on the NO article is impressive: it results in a 0.1 immediate increase to a variable whose daily average is 0.3. This might be due to an increase in the articles about Portugal after a negative market reaction on Spanish bonds.

Figure 6: OIRF from BVAR Daily (Spain)



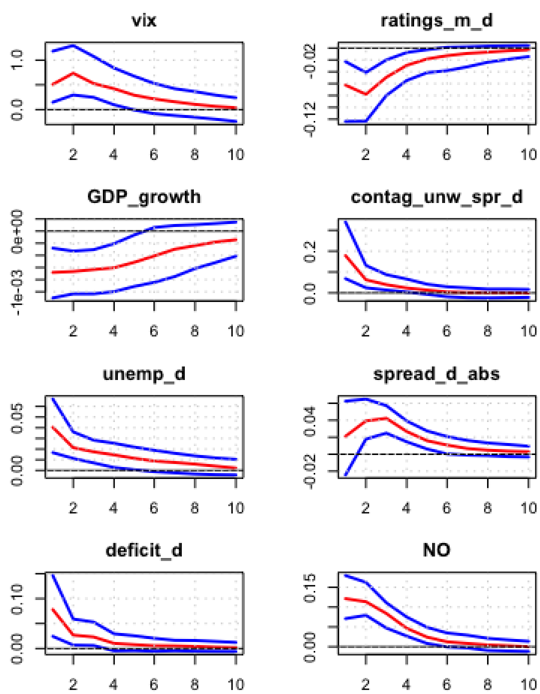
Ireland (Fig. 7) tells us pretty much the same story.

Figure 7: OIRF from BVAR Daily (Ireland)



To recap, both hypotheses seem confirmed for all countries. Unsurprisingly, Greece is the only exception in an otherwise homogeneous pattern. The grouping effect (the NO article shock) on the Greek spread is much smaller (a 2 basis point at best, with a 23 average daily change in basis points). I do not show it here, but with a 90 percent credible interval error band, the IRFs for Greece become barely (but still) significant, while those for the other countries remain highly significant. The spread shock is also much more subdued relative to the other countries. It is likely to be incorrect to infer that developments in Greece did not affect the volume of articles classifying the other countries as PIIGS. Actually, the IRF for Greece are still impressive if one takes into account that the period covers until the end of 2015, while we know that the last part of the crisis was only about Greece. As Fig. 1 shows, there was almost no article mentioning the PIIGS acronym in late 2014 and 2015.

As discussed in the previous section, recursive identification is not the only possible strategy for structural analysis. The next figure shows the IRF for the NO article shock derived from the sign identification pattern described previously. Unfortunately, I cannot find a way to conveniently extract only the IRF of interest (the effect of NO article shock on a country's spread), and I will have to show the IRF for all variables... Since showing all of them would cover too much space (4 countries x 3 datasets), I do so only for the case of Spain (monthly). The only IRF we are interested in is in row 3, column 2. The results are similar to the previous one: a significant increase in the target country's risk premia that lasts for 5 months. Bear in mind that, while the other IRFs are constrained to be of that sign for the first two periods (see the table), the variable of interest is left unrestricted. Hence, the positive increase in the first two periods (albeit only significant in the second) is entirely borne out from the data (of course, conditional on the "correct" sign restrictions for the other regressors). Finally,



7 Robustness

7.1 Placebo Cyprus (planned)

I would like to run the analysis for Cyprus as the other financially strained country, but not part of the PIIGS acronym. I cannot find the data for Cyprus...

7.2 Generalized IRF (planned)

Given the difficulty in justifying the economic rationale for a given ordering (in the Cholesky decomposition) or temporal restriction (in the sign restrictions approach), it is usually suggested to check the results via a generalized impulse response function that is invariant to variable ordering (Antonakakis and Vergos (2013)). The intuition underlying the GIRF is that, instead of shocking all the elements of the residuals vector, Pesaran and Shin 1998 suggest to shock only the residual in the equation of (major) interest and integrate out the effects of the other shocks using the historically observed distribution of the errors [44]. The main advantage of the GIRF is that it avoids the issue of specifying a variable ordering on whcih different scholars may disagree with. However, GIRFs are more difficult to interpret substantively as they represent impulse responses to non-orthogonal shocks Eickmeier and Ng 2015. I think it will be important to show the GIRF results at least in the appendix. Now I need to figure out how to do it...

7.3 Linear interpolation (planned)

So far, variables at lower frequency have been treated as constant for the intermediate periods. The rationale is that investors should update their assessment of a country's relative risk once that information becomes available. Nevertheless, while sound in principle, it is clear that in an information-rich environment investors are hardly taken off surprise by the official announcements regarding macroeconomic factors. In light of this fact, some scholars have suggested to linearly interpolate variables at lower frequency (D'Agostino and Ehrmann (2014)[45]. I have generated new variables with both linear interpolation and spline interpolation, although I have not repeated the analysis with the interpolated variables yet.

[44] As Sims (1980) noted long ago, the variable ordering does not matter if and only if the covariance of the VAR residuals is zero. Consequently, the OIRF and the GIRF will be the same if the variance covariance matrix of the errors is diagonal.

[45] Two other alternatives exist but are not explored further in this paper. First, one could use forecasting values instead of official releases. Second, one may use mixed-frequency models that explicitly account for the different frequencies of the variables.

7.4 Other contagion variables

In the main analysis, the standard contagion channel was accounted by controlling for the unweighted average of the other member countries' spread. Nevertheless, one may argue that a weighted combination is better (Hondroyiannis et al. 2012). Alternatively, one may leave all the remaining PIIGS members' sovereign bonds variables as endogenous variables to account for spillover effects (Galariotis et al. 2016). While this strategy is more comprehensive as it fully specifies the effects of spillover from any other PIIGS country, it also decreases efficiency as the spread variables among countries in the sample period are collinear. For this reason, I opted for summarizing the variables via PCA. All the robustness checks for this and the other contagion variables are in the appendix, except for the trade weighted sovereign bond average, which I have not done yet.

7.5 Levels and changes (planned)

Differencing a fractionally integrated variable risks artificially imposing a moving average structure (CIT NEEDED). While inference is complicated by the presence of variables integrated of order 1, we should bear in mind that the asymptotic results do hold regardless of the order of integration (Bouvet et al. 2013). Following common practice in the literature (Spyrou 2013) I will repeat the previous analysis keeping all the variables in levels. Maybe not needed...

8 Conclusion (not yet)

As Bourdieu (1977) (p. 165) suggested decades ago: "the specifically symbolic power to impose the principles of construction of reality - in particular social reality - is a major dimension of political power".

As Brooks et al. 2015 note, Southern EU governments put a non trivial effort in differentiating their countries from their neighbors in the eyes of foreign investors. To some extent, the results presented in this paper vindicate this rhetorical strategy.

9 APPENDIX

9.1 Granger Causality in Weekly and Daily Dataset

Table 4: Granger Causality in Weekly Panel Dataset

Direction of the Relationship	Controls	P-values
NO ⇒ 10-yrs Bond		**0.000 (t-1)**
		0.609 (t-2)
	✓	**0.000 (t-1)**
	✓	0.776 (t-2)
	✓	**0.000 (t-3)**
10-yrs Bond ⇒ NO		**0.000 (t-1)**
		0.378 (t-2)
	✓	**0.000 (t-1)**
	✓	0.667 (t-2)
	✓	**0.000 (t-3)**

Notes: The optimal lag length is determined independently in each equation by minimizing the Bayesian Information Criterion. The maximum length is set to 4 (one month) for the weekly dataset. All control variables - exogenous and endogenous - are included.All models allow for cross-sectional heteroskedasticity.

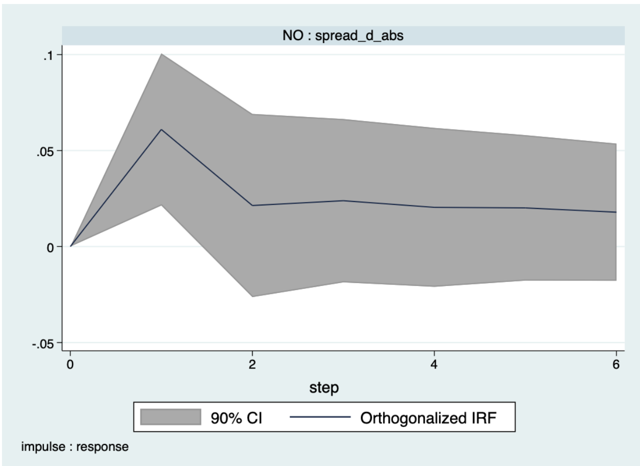
Table 5: Granger Causality in Daily Panel Dataset

Direction of the Relationship	Controls	P-values
NO ⇒ Spread from other PIIGS		**0.000 (t-1)**
		0.605 (t-2)
	✓	*0.052 (t-1)*
	✓	0.242 (t-2)
	✓	**0.000 (t-3)**
Spread from other PIIGS ⇒ NO		**0.004 (t-1)**
	✓	**0.013 (t-1)**
	✓	0.747 (t-2)
	✓	**0.003 (t-3)**

Notes: The optimal lag length is determined independently in each equation by minimizing the Bayesian Information Criterion. The maximum length is set to 5 (one working week) for the daily dataset. All control variables - exogenous and endogenous - are included. All models allow for cross-sectional heteroskedasticity.

9.2 Panel VAR OIRF for model augmented with KOF Monetary Policy Coummunication

Figure 8: OIRF from pVAR Monthly



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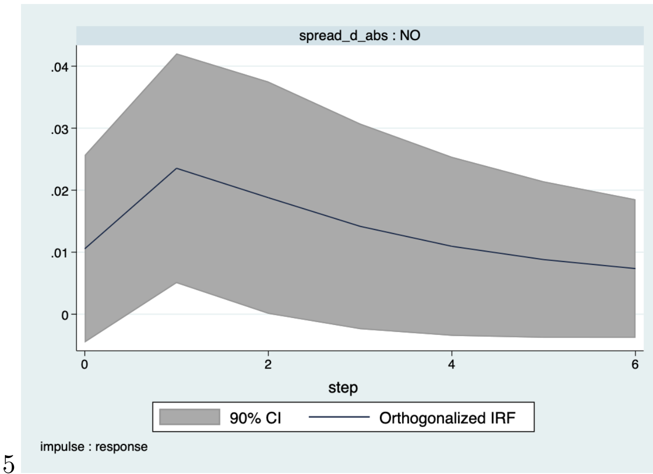
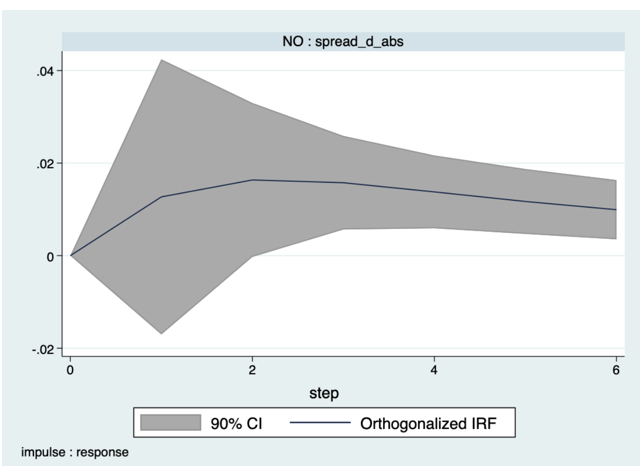


Figure 9: OIRF from pVAR Weekly



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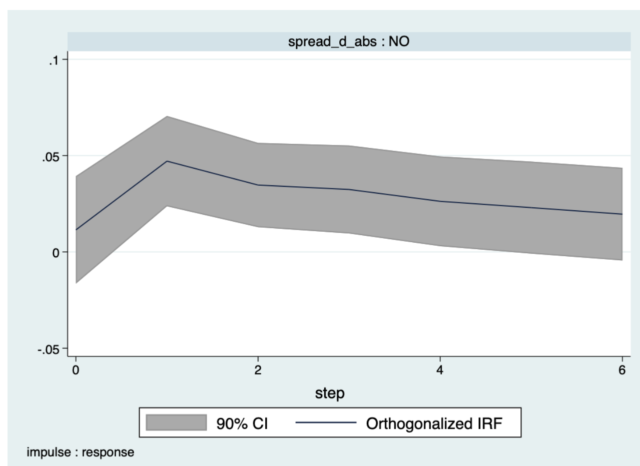
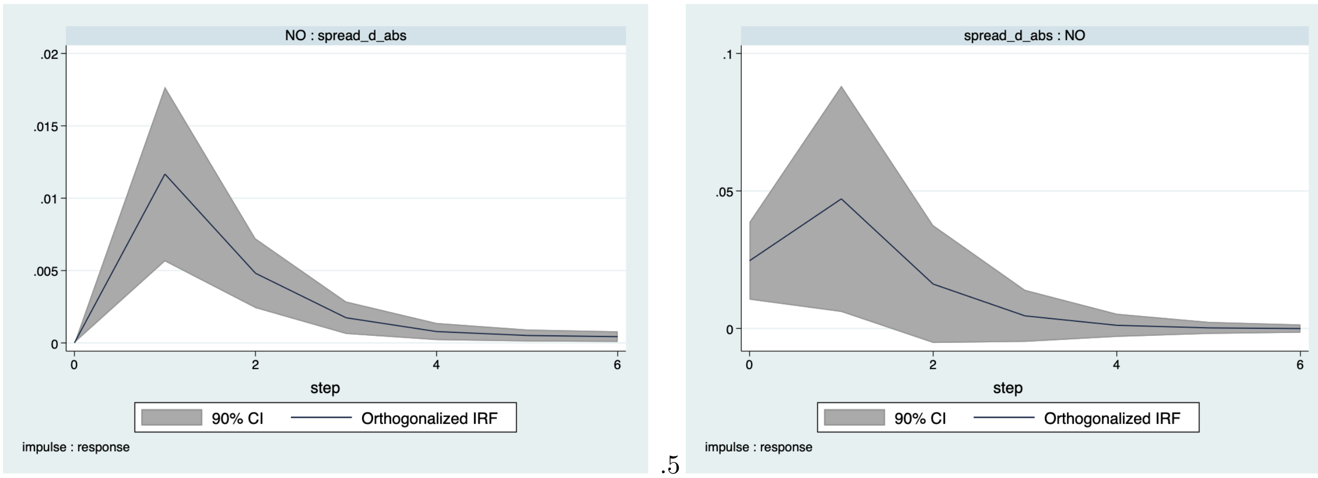


Figure 10: OIRF from pVAR Daily



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9.3 Panel VAR OIRF for Alternative contagion variables

9.3.1 First Principal Component of Other Countries' Credit Rating (exogenous) - Monthly (first row), Weekly (second row), Daily (third row)

Figure 11: OIRF from pVAR Monthly

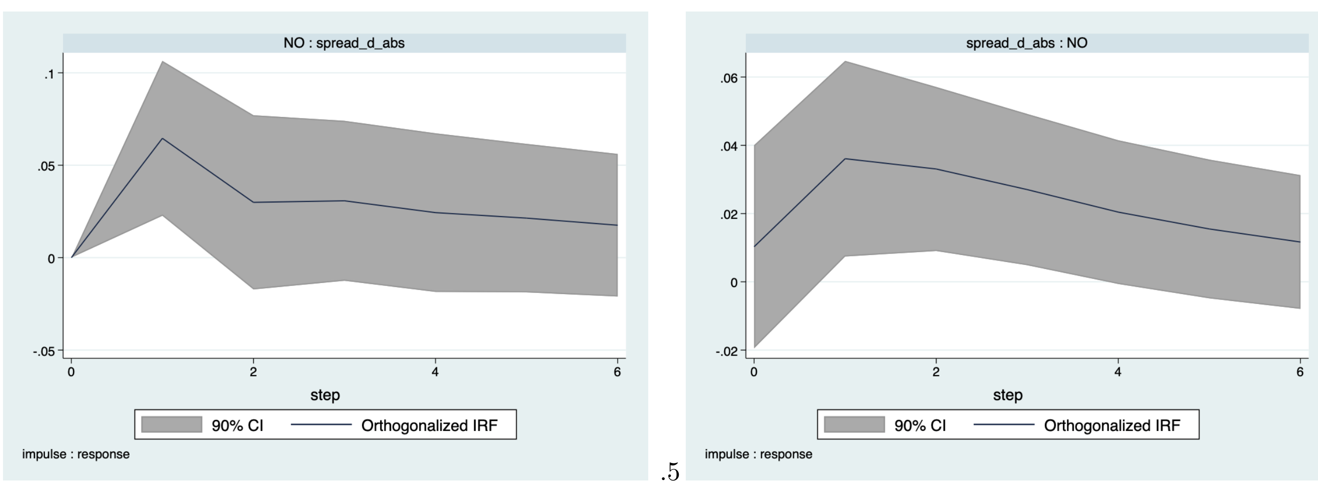

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Figure 12: OIRF from pVAR Weekly

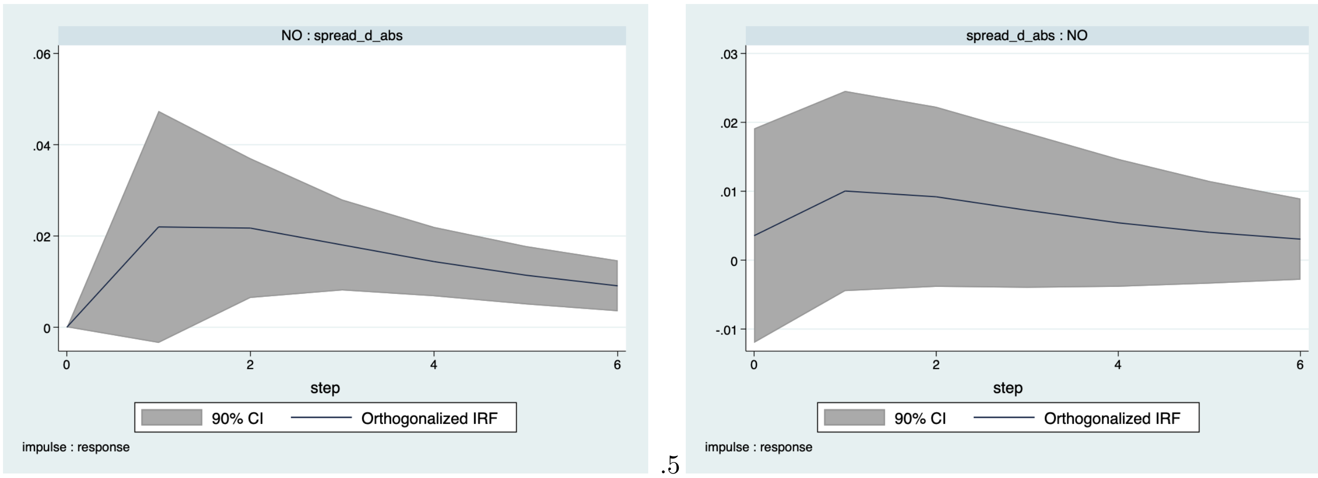

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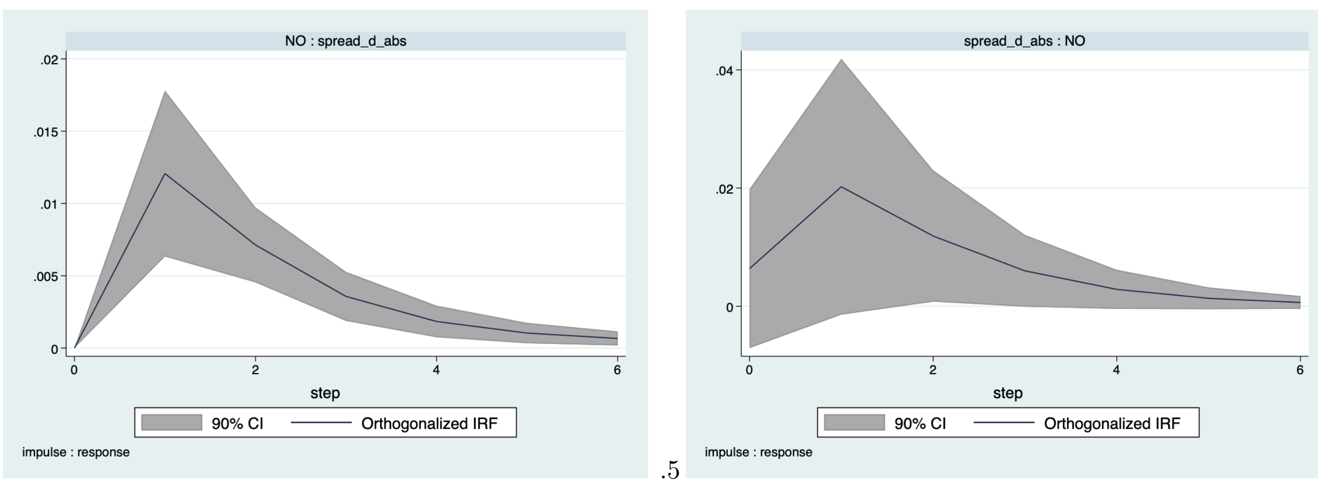
Figure 13: OIRF from pVAR Daily



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9.3.2 Weighted by Financial linkages (Measure 1

Figure 14: OIRF from pVAR Monthly

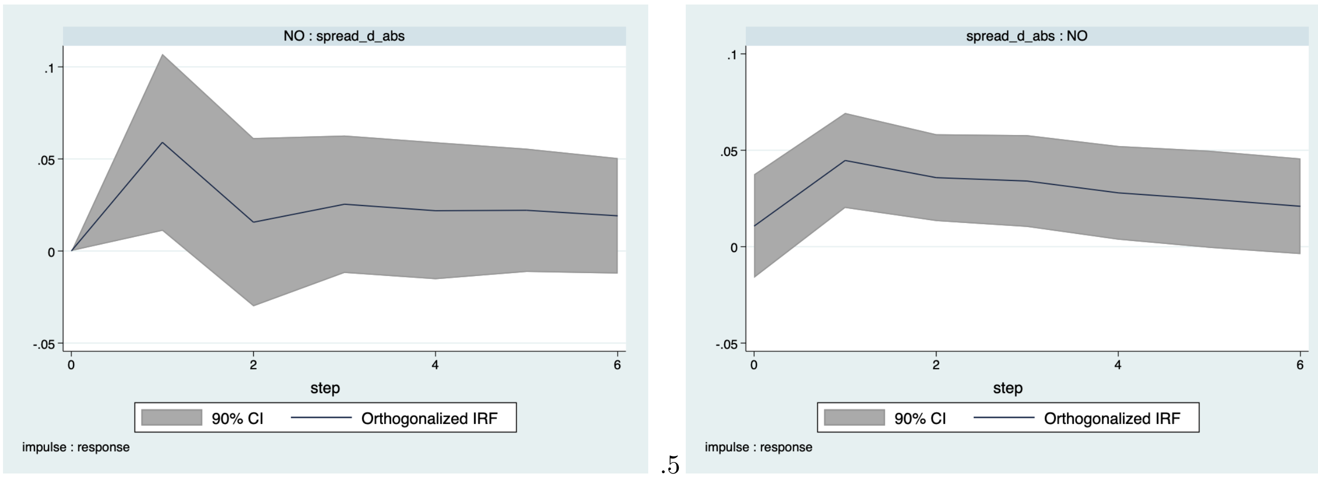

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Figure 15: OIRF from pVAR Weekly

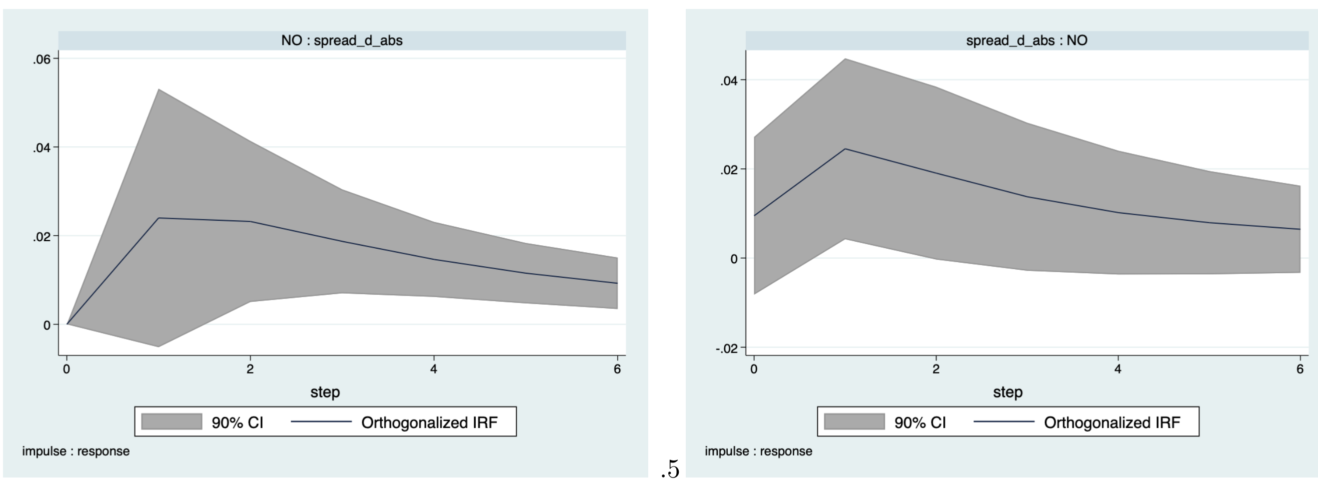

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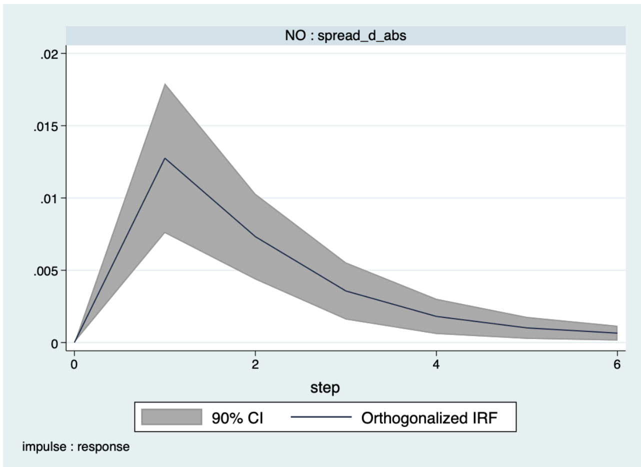
Figure 16: OIRF from pVAR Daily



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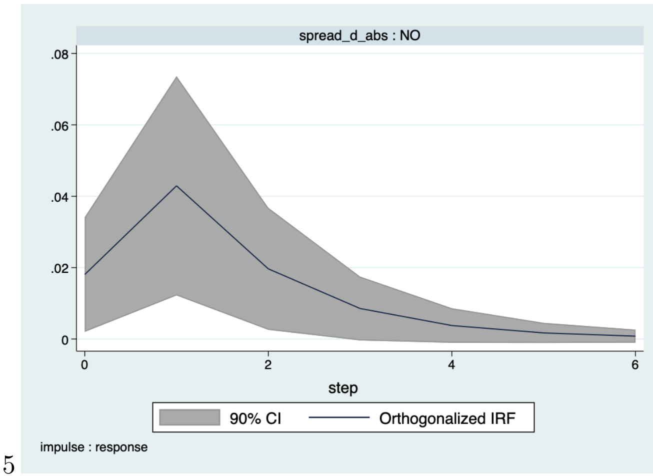
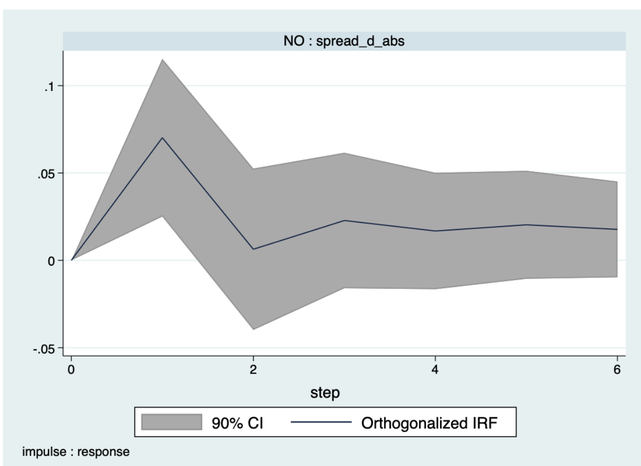


9.3.3 Weighted by Financial linkages (Measure 2

Figure 17: OIRF from pVAR Monthly



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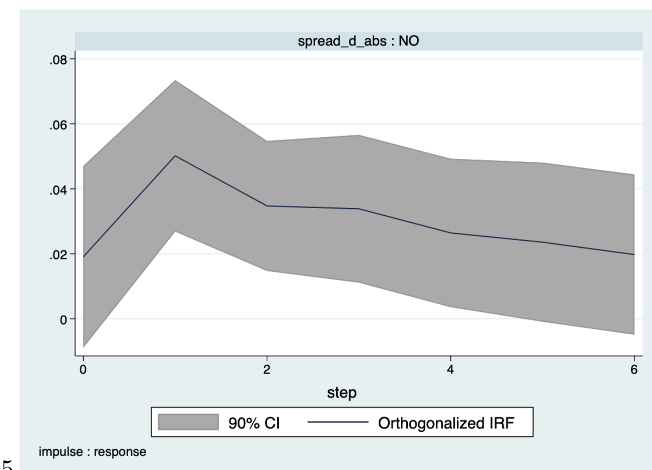

Figure 18: OIRF from pVAR Weekly

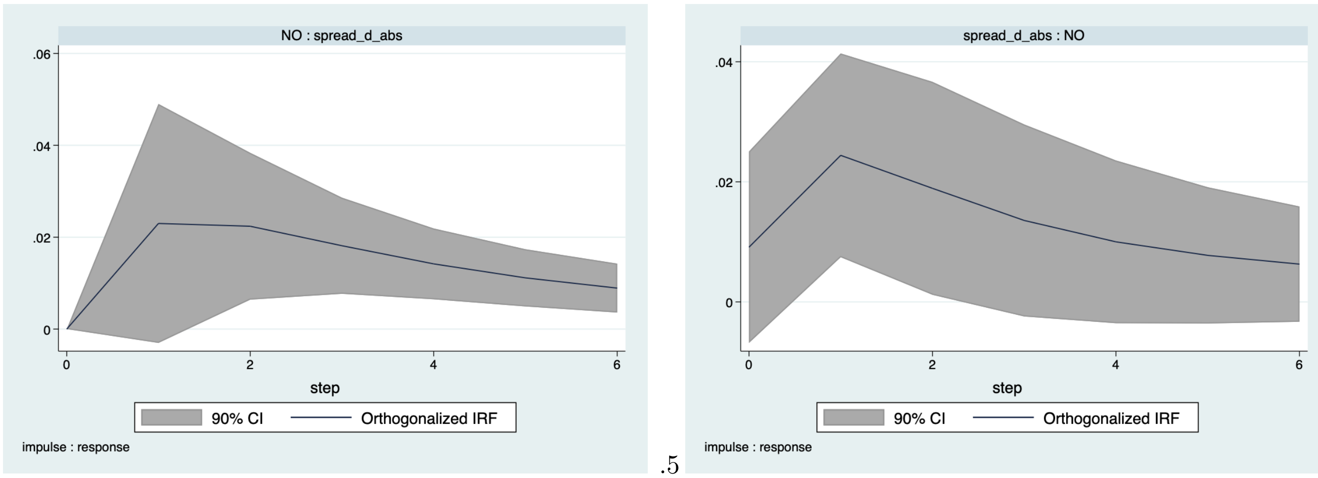

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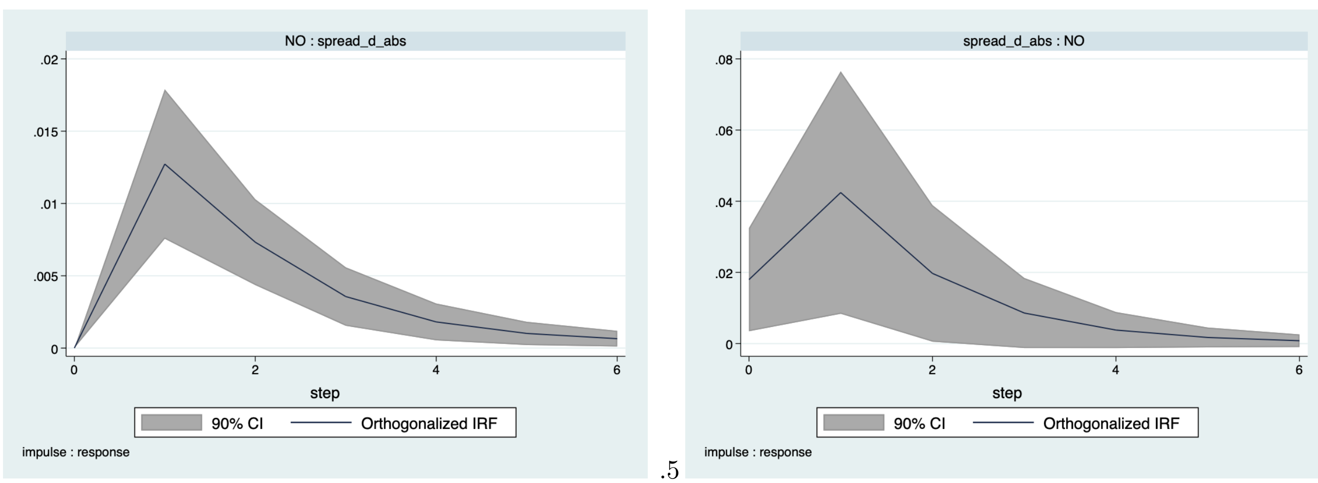
Figure 19: OIRF from pVAR Daily



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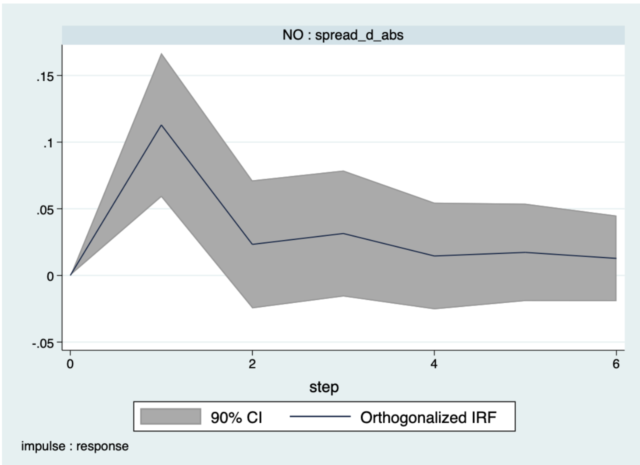
9.3.4 First Principal Component of Other Countries' spread

Figure 20: OIRF from pVAR Monthly



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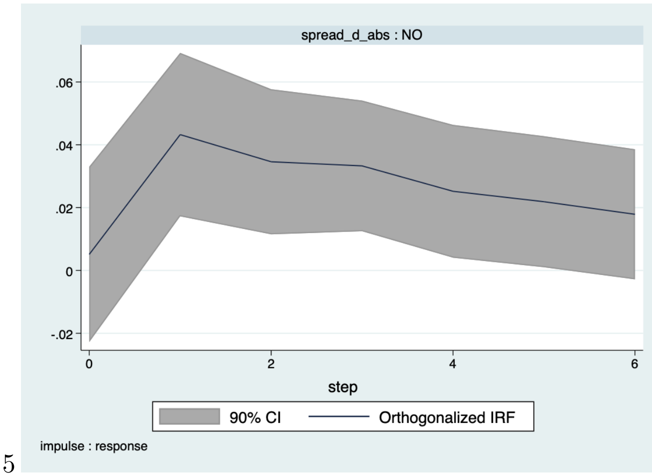
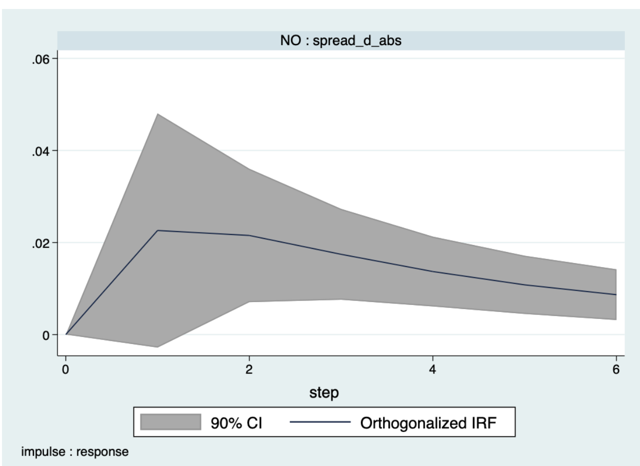


Figure 21: OIRF from pVAR Weekly



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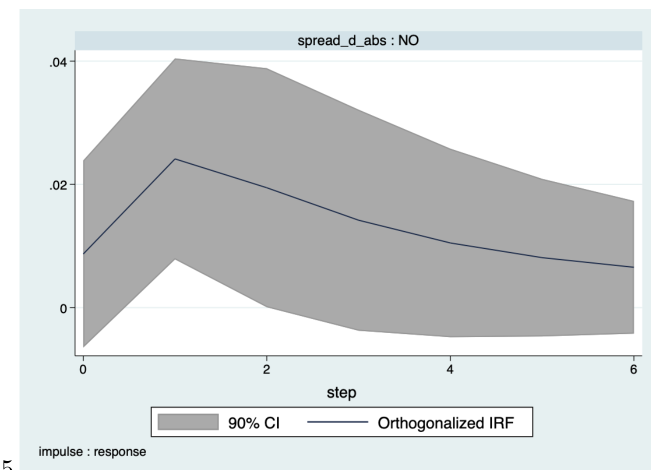
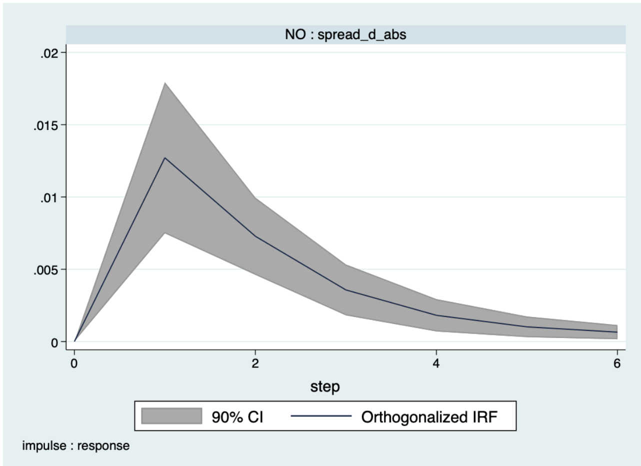


Figure 22: OIRF from pVAR Daily



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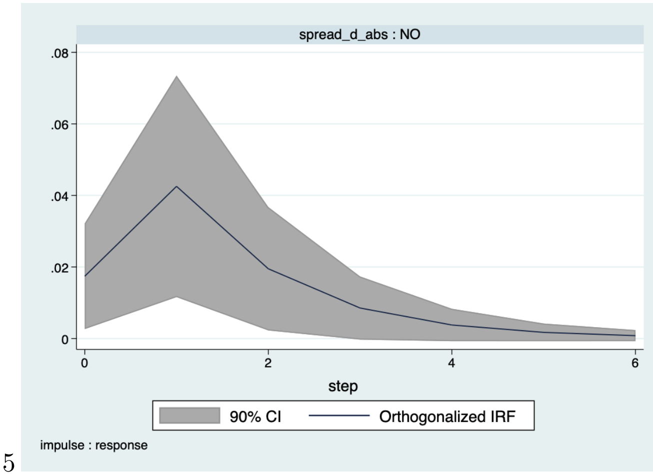
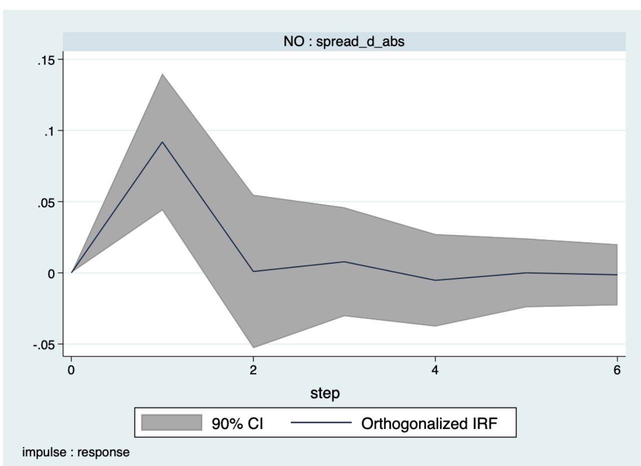


9.3.5 First Principal Component of Other Countries' spread and First Principal Component of Other Countries' Ratings (exogenous)

Figure 23: OIRF from pVAR Monthly



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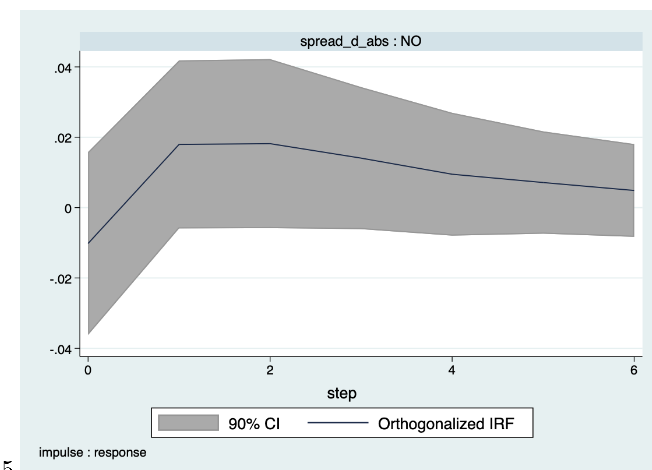

Figure 24: OIRF from pVAR Weekly

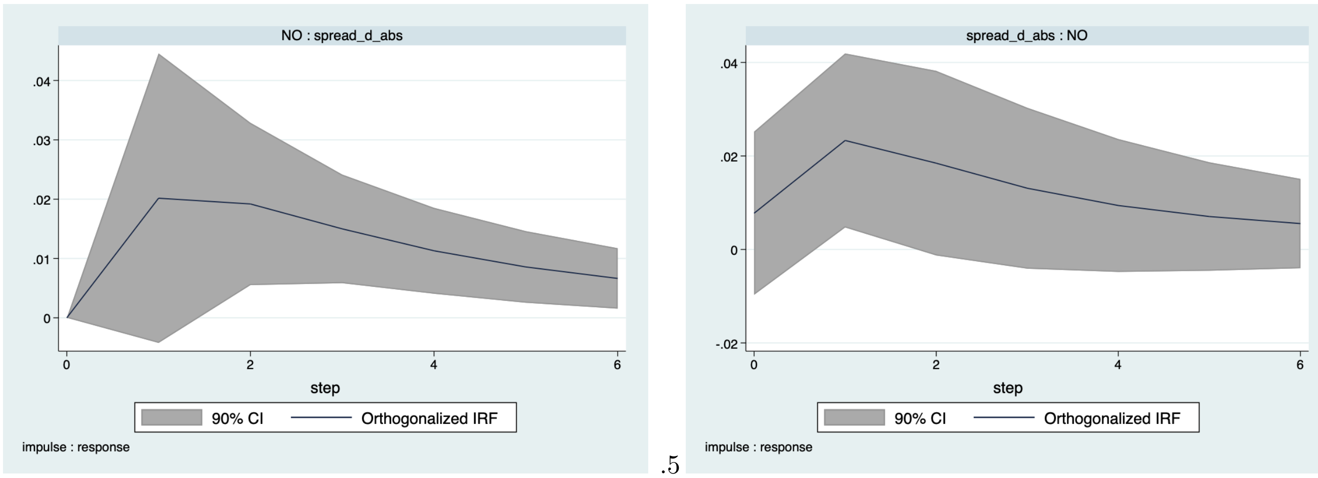

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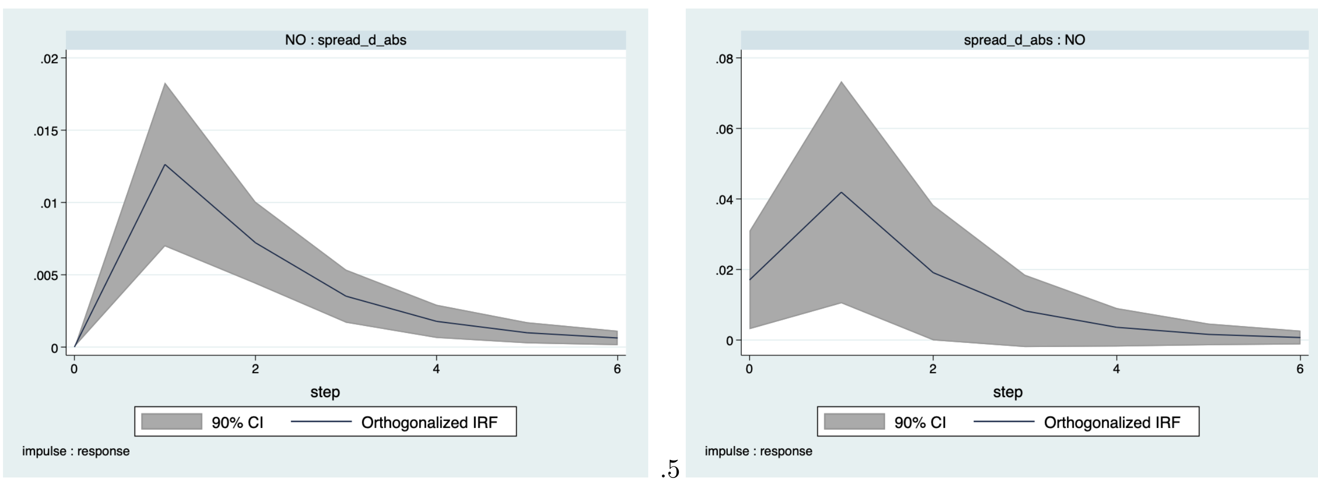
Figure 25: OIRF from pVAR Daily



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9.4 Single country BVAR for Monthly and Weekly Datasets

Figure 26: OIRF from BVAR Weekly (Greece Left, Italy Right)

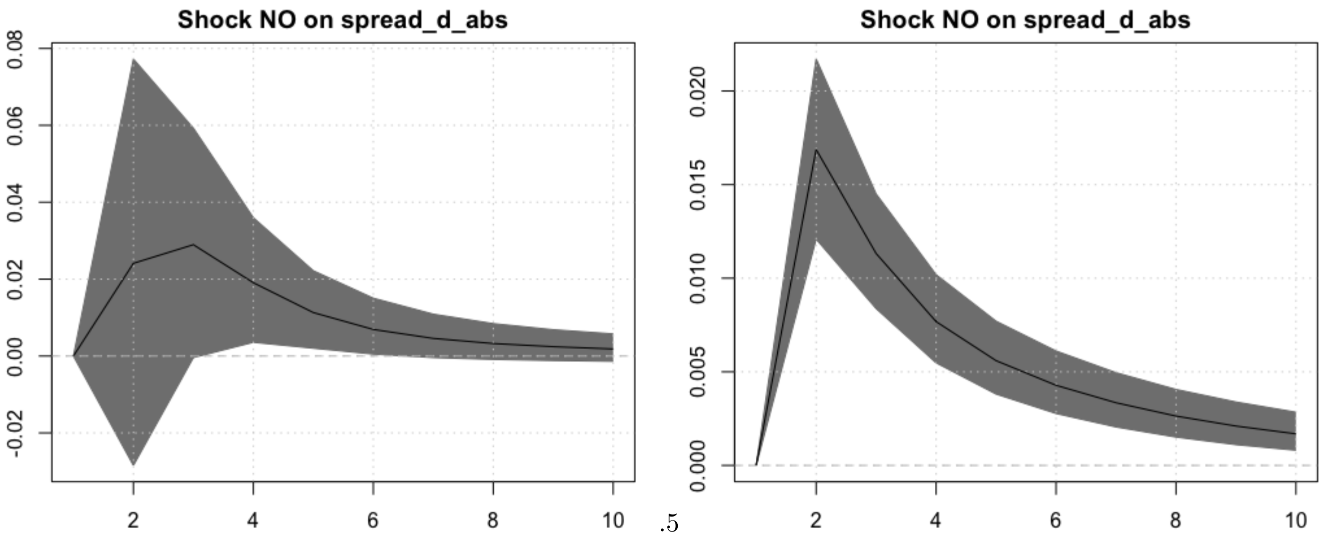

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Figure 27: OIRF from BVAR Weekly (Spain Left, Ireland Right)

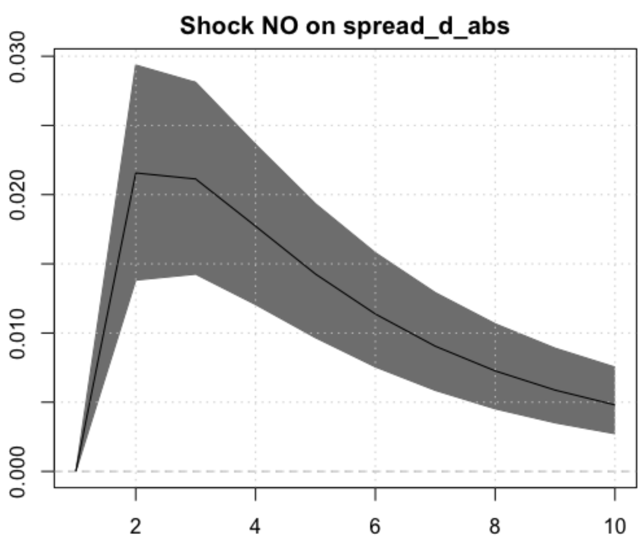

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Figure 28: OIRF from BVAR Monthly (Greece Left, Italy Right)

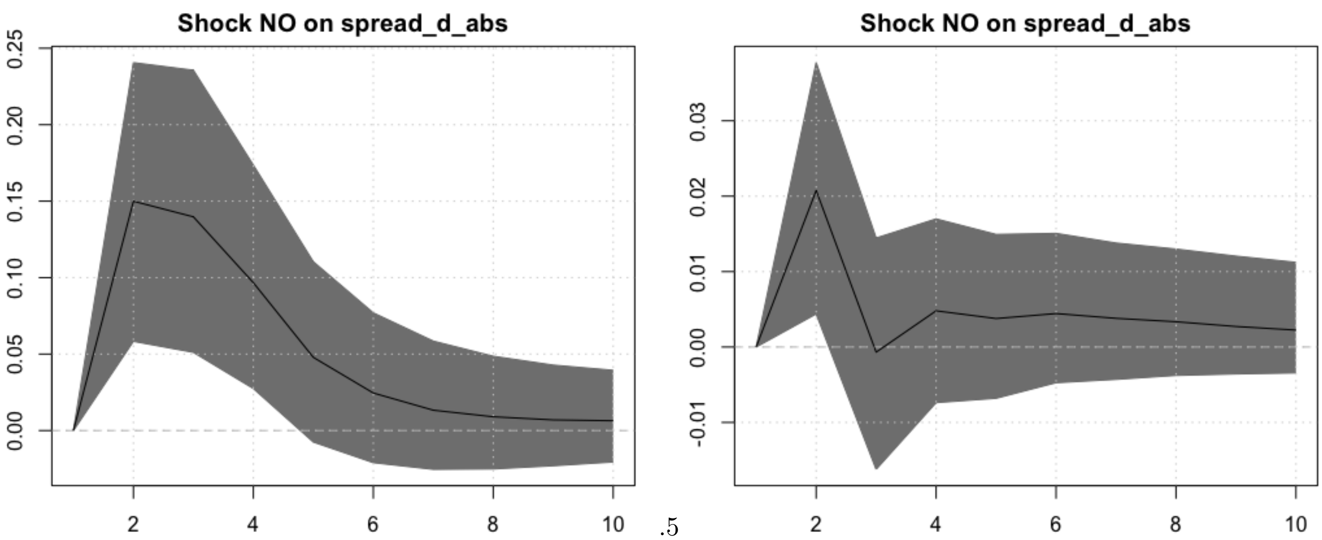

Figure 29: OIRF from BVAR Monthly (Spain Left, Ireland Right)

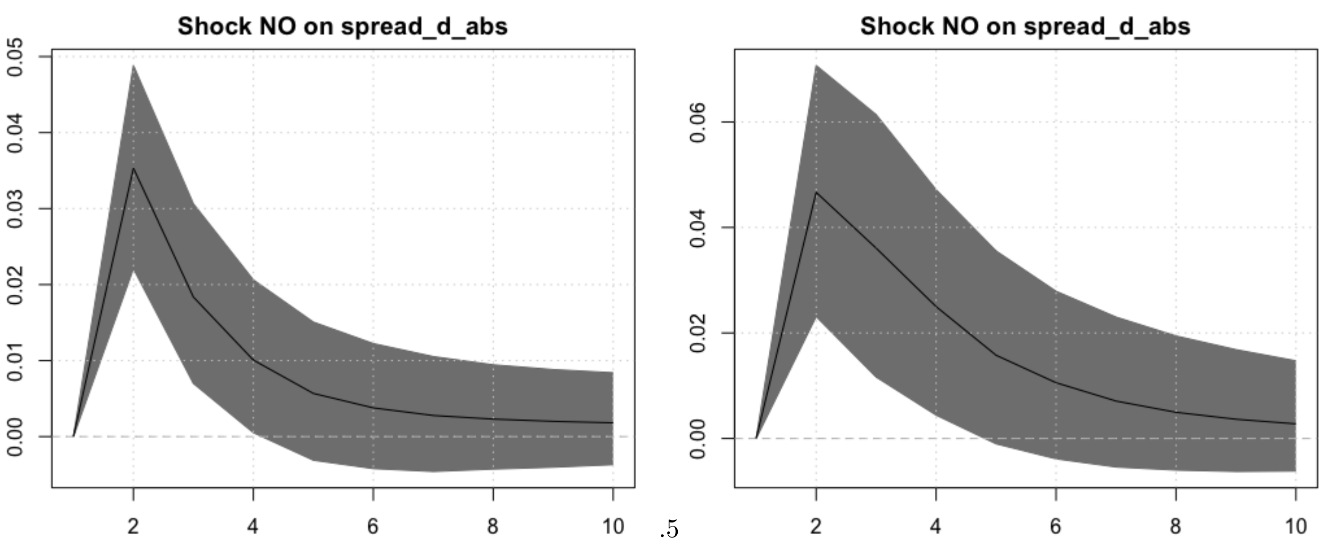

Figure 30: OIRF from BVAR Weekly (Greece Left, Italy Right)

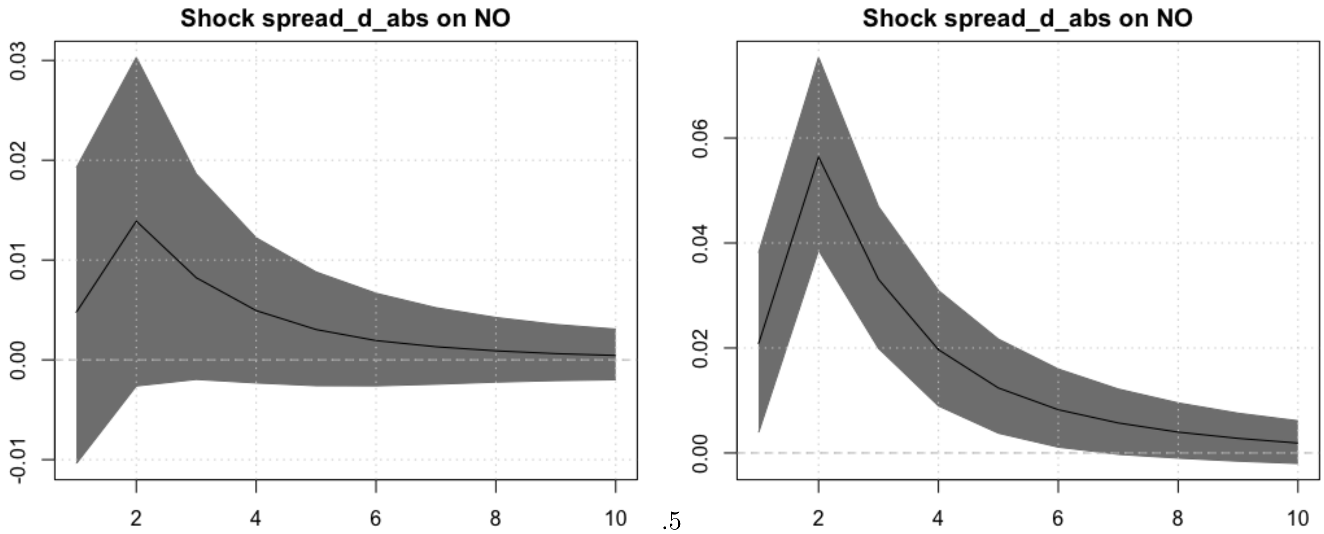

Figure 31: OIRF from BVAR Weekly (Spain Left, Ireland Right)

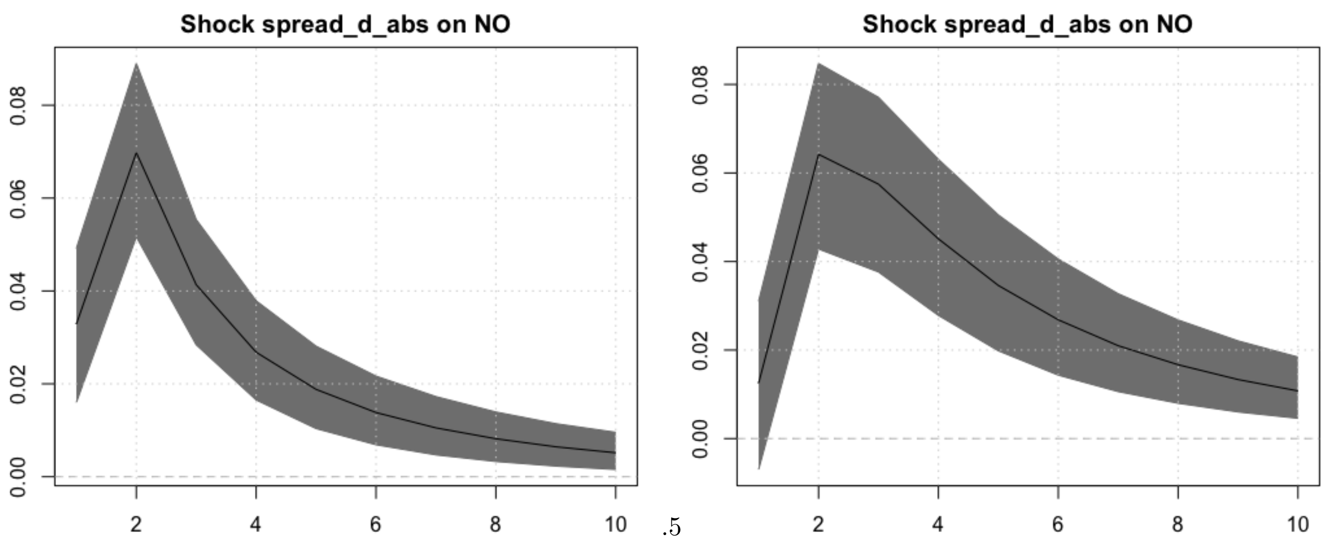

Figure 32: OIRF from BVAR Monthly (Greece Left, Italy Right)

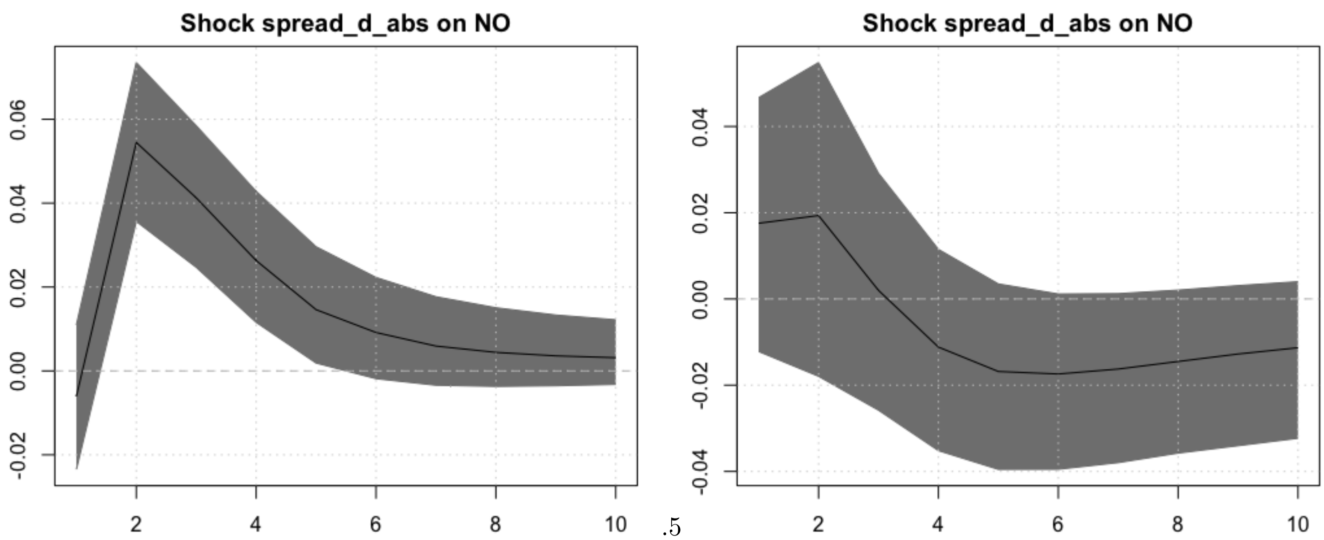

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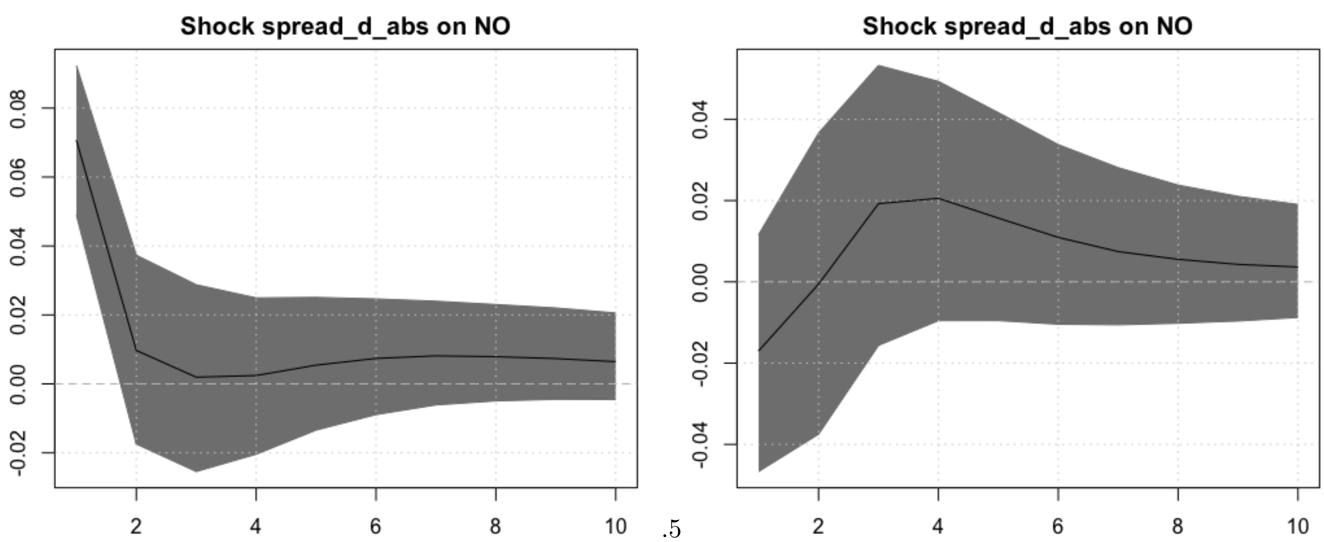
Figure 33: OIRF from BVAR Monthly (Spain Left, Ireland Right)



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