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Essays on Sovereign Debt Crisis

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Contents

1 Lenders' Expectations and Sovereign Debt Crises Contagion **9**

1.1 Introduction 3

1.2 Data Description and the Imprecision Measure Definition 6

1.3 Difference in Banks' Forecasts during the European Financial Crisis . . . 7

1.3.1 Definition 7

1.3.2 Bank Forecasts Correlation with Greek Sovereign Bond Yield . . . 9

1.3.3 Eurozone Core and Outside the Crisis Period 11

1.4 Changes in Banks' Portfolios 13

1.5 Potential Rationalizations 15

1.5.1 Main Potential Explanation 15

1.5.2 Alternative Potential Rationalization: Rational Investors and Information Frictions 18

1.6 Penitential Rationalizations and the Data 18

1.6.1 Additional Definitions 18

1.6.2 Heterogeneity on Bank Reaction after Observing a Greek News . 19

1.7 Stylized Model 21

1.7.1 Countries 21

1.7.2 Lenders 22

1.7.3 Endowment Process 23

1.7.4 Information Structure 23

1.7.5 Timing 24

1.7.6 Countries' Recursive problem 24

1.8 Simulations 26

1.8.1 Calibration . . . 26
1.8.2 Simulations . . . 28
1.9 Conclusion . . . 30
1.10 Appendix . . . 38
1.10.1 Appendix 1: Bank Imprecision Indicator . . . 38
1.10.2 Appendix 2 A: Robustness check: Robustness check: Different Precision Indicators . . . 39
1.10.3 Appendix 2 B: Robustness check: Different Crisis Period . . . 40
1.10.4 Appendix 2 C: Dynamic Difference in Difference . . . 43
1.10.5 Appendix 2 D: Dynamic Differences in Differences Robustness checks 45
1.10.6 Appendix 3: Additional Evidence Syndicated Loan Market . . . 47
1.10.7 Appendix 4: Alternative Potential Rationalization Diagnostic Expectations . . . 48
1.10.8 Appendix 5 B: Heterogeneity on Bank Reaction Beyond Greek News 50
1.10.9 Appendix 5 D: Banks reaction to local news . . . 50
1.10.10 Appendix 6: Magnitude of the forecast errors during the crisis . . . 52
1.10.11 Appendix 7: Correlation Between Greek and Italian GDP Forecast 54

2 Lenders' Inflation Expectations, Credit Allocation and Leverage 57
2.1 Motivation . . . 57
2.2 Methodology . . . 58
2.3 Preliminary Results for US and Canada . . . 61

3 Sovereign Default, Expectations and Contagion 73
3.1 Introduction . . . 74
3.2 Related Literature . . . 75
3.3 The model . . . 76
3.3.1 Endowment Process . . . 78
3.3.2 Information Structure . . . 78
3.3.3 Timing . . . 79
3.3.4 Recursive Equilibrium . . . 79
3.3.5 The Expectation Channel . . . 83

3.4 Preliminary Model Simulation 85
3.4.1 Calibration 85
3.4.2 Simulations 86
3.5 Conclusion and Potential Extensions 87
3.6 Tables and Figures 96
3.7 Appendix 1 100

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Introduction

This thesis contains three chapters. The first one, which is the main one, investigates the role of lenders' expectations in propagating the Greek sovereign debt crisis within the Eurozone periphery. It documents which type of lenders contribute most to the spreading, provides a rationalization, and quantifies the effect on countries' default probabilities. Using data from Consensus Economics survey, I classify lenders according to their GDP forecast precision before the Greek sovereign debt crisis started. During the Greek crisis, the less precise lenders changed their forecast and portfolio against the rest of the Eurozone periphery more than the more precise ones. The rationalization with more empirical support is that less precise lenders present a stronger forecast correlation across Eurozone periphery countries' GDP than the more precise lenders. Thus, upon receiving news about Greece, the former update their forecast for the rest of the Eurozone periphery relatively more. I introduce this mechanism in an otherwise standard quantitative sovereign default model; in this economy, the country faces a price schedule almost 4 percent lower than in the rational lenders' benchmark.

The second chapter is a joint work with Filippo de Marco. We analyze the role of expectations in bank lending in the context of an inflation increase. Banks that expect a higher inflation increase their lending to indebted companies with respect to banks that expect a lower inflation.

The last chapter studies the contagion of the Tequila Crisis to Argentina through two countries' endogenous default model, where countries' fundamentals are correlated. International rational lenders incorporate a country's debt decision to update their expectations about the other country's fundamentals and, ultimately, its default probability.

Chapter 1

Lenders' Expectations and Sovereign Debt Crises Contagion

Lenders' Expectations and Sovereign Debt Crises Contagion

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Abstract

This paper investigates how lenders' expectations may have fueled the propagation of the Greek crisis to other Eurozone periphery countries (i.e., Italy, Spain, Ireland, and Portugal). Using data from the Consensus Economics survey, I classify lenders by their GDP growth forecast precision before the crisis. During the crisis, less precise lenders adjusted their GDP growth and sovereign bond yield forecast against the rest of the Eurozone periphery relatively more than their more precise counterparts. Consequently, less precise lenders also shifted their portfolios away from the Eurozone periphery countries relatively more. In line with a model where some lenders rely on broad categories, such as the Eurozone periphery, the less precise lenders display a stronger GDP forecast correlation between Greece and other Eurozone periphery countries, driving these empirical results. By incorporating this mechanism into a two-country sovereign default model, I quantify that less precise lenders might have reduced Italian bond prices by almost 11 percent more than Bayesian lenders.

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1 Introduction

Sovereign debt crises may propagate across borders through shifts in lenders' expectations about other countries' fundamentals, as (Kaminsky et al., 2003; Cole et al., 2024) highlight. A sovereign debt crisis may raise lenders' concerns about other countries' debt sustainability, inducing lenders to demand higher returns and, ultimately, pressuring these countries' debt rollover processes. While this contagion channel is intuitive, it has not been examined using lenders' expectation data. This paper aims to fill this gap.

The Greek sovereign debt crisis contagion to the rest of the Eurozone periphery (Italy, Spain, Ireland, and Portugal) is a key example of crisis spreading.[1] Figure 1 provides an overview of the crisis timeline and sovereign bond yields: in October 2009, a new Greek government revealed that the previous administration had manipulated fiscal data, masking a significant portion of the country's debt. This disclosure marked the beginning of the Greek sovereign debt crisis. Following this event, sovereign bond yields in other Eurozone periphery countries surged, while Eurozone core countries, such as France and Germany, saw no similar increase.[2] In July 2012, Draghi's "Whatever it Takes" announcement led to a decline in the yields of Greece and the rest of the Eurozone periphery countries.

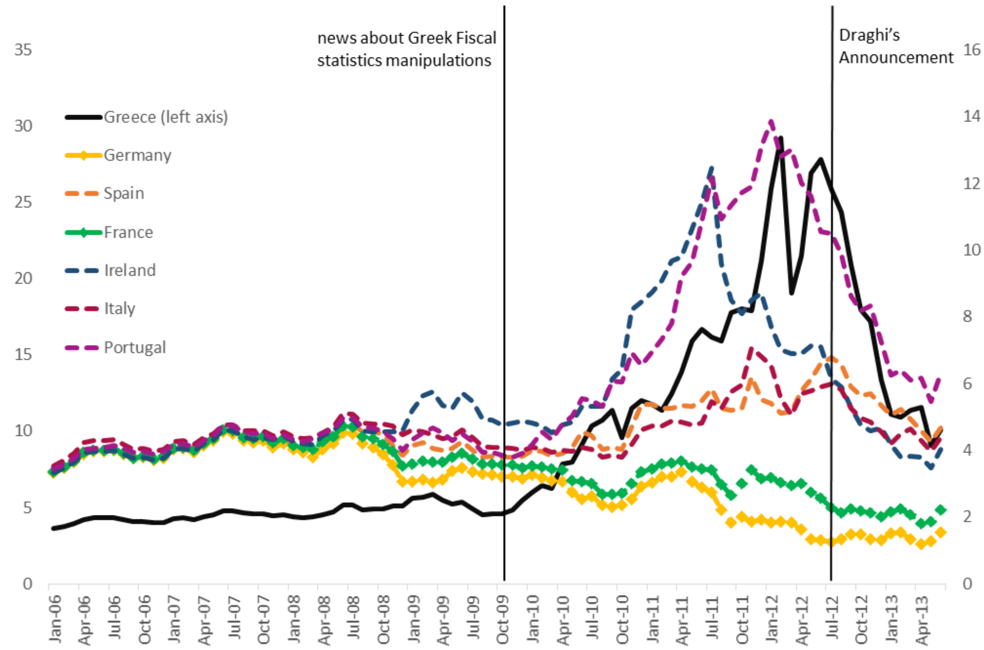
This paper examines how lenders' expectations contributed to the Greek crisis's spread to the rest of the Eurozone periphery. Using data from the Consensus Economics survey, I construct an imprecision measure based on banks' real GDP growth forecast errors before the crisis. I document two key findings: (i) less precise banks—those with greater forecast errors—adjusted their expectations about the Eurozone periphery more negatively than more precise banks, and (ii) these less precise banks also shifted their portfolios away from the Eurozone periphery more significantly. I focus on banks because, during the crisis, they held a sizable portion of Eurozone periphery sovereign bonds on their balance sheets (De Marco, 2019; de Haan and Vermeulen, 2021) and they regularly report their expectations and sovereign bond holdings.

The empirical findings align with evidence that banks often categorize investment opportunities broadly (Swensen, 2009). Those using coarser categories (e.g., Eurozone periphery) tend to

[1]Other examples of contagion include the Tequila Crisis, which began in Mexico and spread to the rest of Latin America, and the Thai financial crisis, which spread throughout Southeast Asia.

[2]The Eurozone core countries for which Consensus Economics reports banks forecast during the period of analysis are: Germany, Netherlands, France, Austria, Belgium, and Finland.

Figure 1: Countries' Sovereign Bond Yields



Source: European Central Bank. Note: This figure shows the countries' sovereign 10-year maturity bond yield on the last day of the month around the Greek crisis. Greek sovereign bond yield is on the left vertical axis, and the other countries' yields are on the right axis.

produce less precise forecasts and perceive a higher correlation among countries' fundamentals in the category. Consequently, when news emerged about Greece, these banks adjusted their expectations and portfolios more drastically for the rest of the Eurozone periphery than banks with finer categorizations (which produce more precise forecasts).

To quantify the contribution of less precise lenders to the spread of the Greek crisis, I develop a two-country sovereign default model in which lenders receive a signal about one country (A) and update their beliefs about both countries A and B. In this model, lenders with imprecise beliefs—who overestimate the correlation between countries' fundamentals—respond to negative signals about Country A by lowering their expectations for Country B's endowment more than Bayesian lenders would. Calibrating this model to the Greek crisis, I find that imprecise lenders lowered Italian bond prices by an additional 11 percent compared to Bayesian lenders.

To construct the imprecision measure, I use data from Consensus Economics, which has collected monthly forecasts of macroeconomic variables from banks and institutions since 1989. The imprecision measure consists of banks' GDP average square forecast error for each country before the Greek crisis started. The higher a bank's average squared forecast error for a given country, the less precise the bank is about that country. The imprecision measure is a country-bank indicator (constant over time); for instance, a bank can be more precise about Spain and less precise about Germany. I asses banks' imprecision based on their GDP forecasts because GDP is both the most commonly forecasted variable in the survey and central to sovereign default models, where lenders form expectations about a country's GDP to price its sovereign bonds (Aguiar and Amador, 2020).

The imprecision measure correlates with observable bank characteristics. Banks with larger portfolios in a country or those headquartered there tend to make more precise forecasts about that country. In addition, more imprecise banks exhibit a stronger GDP forecast correlation between Greece and the rest of the Eurozone periphery countries than more precise banks. This finding aligns with models suggesting that coarser categories amplify perceived correlations within groups (Bordalo et al., 2016, 2018). (Barberis and Shleifer, 2003) argue that category-based thinking in banks leads to overestimation of correlations within assets' groups.

To analyze how banks changed their forecasts differently during the crisis depending on the imprecision measure, I regress banks' GDP and sovereign bond yield forecasts on the interaction between the imprecision measure and a crisis indicator, as well as several controls. I consider mainly two crisis indicators: a time dummy variable equal to 1 from October 2009 to June 2012, and 0 otherwise, and the Greek sovereign bond yield, which I interpret as a continuous measure of the severity of the Greek crisis. Hence, the empirical strategy compares the more imprecise banks' forecast adjustments during the crisis with respect to the more precise banks.

The more imprecise banks adjusted their forecast against the Eurozone periphery more substantially during the crisis. In the main specification, a bank one standard deviation more imprecise than the average reduced its GDP forecast about the Eurozone periphery by 0.122 (approximately 25 percent lower than the average forecaster) and increased its sovereign bond yield forecast by 0.123 (approximately 2.5 percent higher than the average forecaster).

Banks' portfolio decisions are aligned with their expectations. Merging Conensus Economics survey with banks' portfolio data from the European banking Autority (EBA), I show that during the crisis, when Greek sovereign bond yields rose, more imprecise banks reduced their sovereign bond holdings from the Eurozone periphery (excluding Greece) relatively more than the more precise banks. I complement these findings with evidence from the syndicated loan market, which provides more comprehensive data.[3] During the crisis, less precise banks raised the interest rates on syndicated loans for companies headquartered in the Eurozone periphery to a greater extent than more precise banks. This evidence is consistent with recent studies showing a strong relationship between investors' forecasts and their portfolio decisions (Giglio et al., 2021; De Marco et al., 2021).

The overall empirical evidence is that, during the crisis, more imprecise banks adjusted their forecasts and portfolios against the Eurozone periphery more than more precise banks. Consequently, the former put more pressure on the debt rollover processes of Eurozone periphery countries. Repeating the same analysis for the Eurozone core, I find virtually no differences across banks' imprecision, whether in forecasting countries' GDP and sovereign bond yields or in rebalancing their sovereign bond portfolios. Reinforcing the idea that the Greek crisis induced more imprecise banks to adjust their forecasts and portfolios more heavily against the Eurozone periphery, but not for other regions.

I interpret the empirical findings as a consequence of more imprecise banks relying on different models compared to the more precise banks, rather than differences in their information sets. Section 5 provides additional evidence supporting this hypothesis. Consistent with prior research showing that sophisticated investors tend to overreact to news (Bordalo et al., 2024a,b), I present suggestive evidence that less precise banks consistently overreact more strongly to news from Greece when forecasting Eurozone periphery countries' GDP, not only during the crisis but over a long period of time.[4] This pattern is difficult to reconcile with the hypothesis of difference in their information sets. Repeating the analyses for the Eurozone core countries, I find virtually no differences across banks' imprecision measure.

Finally, I develop a two-country endogenous default model to analyze to which extent more imprecise lenders contributed to the Greek crisis' contagion. The key difference between this

[3] The syndicated loan market offers monthly data dating back to 1991, whereas data from the sovereign bond market is only available on a quarterly basis starting in 2010. A syndicated loan is a loan made by a group of banks to a company. I consider only the precision of the lead bank in each deal to determine whether less precise banks charged a higher interest rate. There is a strong link between the interest rate a firm faces and that of the country where it operates (Hassan et al., 2021).

[4] Overreaction is typically defined as occurring when an agent, upon receiving news about a variable, consistently provides forecasts that exceed the variable's actual realization.

model and a more standard one (Arellano, 2008) is that lenders misperceive the correlation between countries' endowments: There are common shocks to both countries' endowment processes, which generate a positive cross-country endowments correlation, lenders believe in a higher correlation than the actual one. In addition, lenders observe a signal about one country (A) and update their beliefs about country A's endowment and the common shock size using the Bayesian updating rule. Since lenders believe in a higher endowments correlation, when they observe a signal about country A, they adjust their beliefs about country B's endowment more strongly than a Bayesian lender (who has correct beliefs about the endowment correlations) would do.

The mechanism at the heart of the model is as follows. Countries issue a non-contingency bond, so they have higher default incentives when they receive a low endowment because paying a fixed amount of resources is more costly in terms of utility.[5] Therefore, when lenders expect a lower endowment, they provide a worse price schedule. Since lenders overestimate the cross-country endowments correlation, upon receiving a negative signal about country A, lenders update their expectations about country B more than a Bayesian lender would. As a result, more imprecise lenders provide a worse price schedule for country B, putting additional pressure on its debt rollover process and further increasing its default incentives.

I use the model to quantify the role of more imprecise lenders in propagating the Greek crisis to Italy. The exercise consists in comparing an economy where all lenders are imprecise with another where all lenders are Bayesian. In the first case, I calibrate the lenders' perceived correlation between Italian and Greek endowments to the less precise banks' GDP forecasts correlation between these two countries, while the model's actual endowment correlation is set to the observed GDP correlation between Greece and Italy. Preliminary simulations show that, during the crisis, when all lenders are imprecise, Italy faces a bond price schedule almost 11 percent lower than in the Bayesian lender benchmark. This worse price schedule increases Italy's default incentives by a similar magnitude.

Related Literature. The main contribution of this paper is to introduce individual lenders' expectations into the sovereign default literature. This leads to an empirical contribution, which is the main one, and to propose a complement channel for the contagion.

[5]It is a well-established result that under incomplete markets countries have larger default incentives (Aguiar and Amador, 2020).

Empirically, contagion is often defined as a structural change in the relationship between two countries, where, during a crisis period, these two countries exhibit a higher correlation in sovereign bond yields than in normal times (Forbes and Rigobon, 2002; Caporin et al., 2018; Rigobon, 2019; Favero and Giavazzi, 2002). (Bahaj, 2020) constructs a series of country-specific idiosyncratic shocks that are orthogonal to other countries' fundamentals.[6] During the European sovereign debt crisis, a negative idiosyncratic shock in one country led to an increase in the sovereign bond yields of other Eurozone periphery countries. This paper contributes to this literature by analyzing individual institutional investors' expectations and portfolios to document which types of lenders contributed most to the spread of the Greek crisis.

Several scholars point out the role of lenders expectation in triggering sovereign debt crisis (Eaton and Gersovitz, 1981; Calvo, 1988; Alesina et al., 1989; Cole and Kehoe, 2000; Aguiar and Gopinath, 2006; Lorenzoni and Werning, 2019; Aguiar et al., 2016; Ayres et al., 2018, 2023; Aguiar et al., 2017; Aguiar and Amador, 2020). (Bocola and Dovis, 2019) find that changes in lenders' expectations because of non-fundamentals' news explain 13 percent of the increase in Italy's sovereign default probability during the European sovereign debt crisis. This paper provides empirical evidence on to what extend lenders expectations change during crisis and it quantifies the impact of these changes on default probabilities.

Scholars point out different crisis contagion channels, such as deterioration in local banks' balance sheets (Gennaioli et al., 2014; De Marco, 2019), portfolio re-balancing (Broner et al., 2006; Arellano et al., 2017). The closest channel to this paper's mechanism is the change in expectations through information acquisition (Cole et al., 2022a,b; Ahnert and Bertsch, 2022). This paper provides a complementary mechanism to explain sovereign debt crisis contagion: some lenders overestimate the correlation across countries, hence a crisis in one country may affect these lenders' expectations about other countries' fundamentals, reducing their willingness to lend and thereby increasing the default incentives of these countries.

The rest of the paper is structured as follows: Section 2 presents the data sources and defines the imprecision measure. Section 3 examines forecast changes during the crisis, and Section 4 analyzes portfolio adjustments. Section 5 discusses interpretations of the empirical findings. Section 6 introduces the model, and Section 7 presents preliminary calibrations and simulations. Finally, I

[6]The shocks are primarily related to political issues, such as Catalonia's request for financial aid from the Spanish central government on August 28, 2012.

conclude with the broader implications of these findings.

2 Data Description and the Imprecision Measure Definition

This section presents the data sources, defines the imprecision measures, and provides descriptive statistics. I combine mainly three sources of data to conduct the empirical analysis: (i) the Consensus Economics survey for the banks' forecasts, which is the main source, (ii) the European Banking Authority (EBA) for banks' holdings of sovereign bonds, and (iii) LPC Dealscan for the Syndicated loans data.

2.1 Data Sources Description

The Consensus Economics survey collects and reports monthly forecasts from institutions and banks for various macroeconomic variables. The sample consists mainly of developed economies. The data started in October 1989, and the number of countries included in the sample has increased over time. Initially, in 1989, forecasts were available for only seven countries, three of which were from the Eurozone.[7] By 2005, all current Eurozone countries were included in the sample. When a country is incorporated into the sample, multiple banks provide forecasts for it, resulting in a relatively stable number of forecasters over time.[8] Appendix 1 presents the evolution of forecasters for each country.

Banks' forecasts are collected at the beginning of each month and published during the second week. This timing gives banks approximately two weeks to act on their forecasts before they become public. Additionally, prizes are awarded to the most accurate forecasters, providing an incentive for banks to report their true expectations. This data source has been widely used to address macroeconomic questions: (De Marco et al., 2021) shows that banks' sovereign bond yield forecasts influence their portfolio decisions; (Kalemli-Özcan and Varela, 2021) uses bank exchange rate expectations to analyze uncovered interest parity, and De Marco and Friedheim (2024) use this data to study banks' inflation forecasts and their credit allocation to highly leveraged firms.

[7]The countries forecasted in 1989 included those that would later join the Eurozone: Germany, France, and Italy, as well as four countries that would not: Canada, Japan, the United Kingdom, and the United States of America.

[8]The median country is incorporated into the sample with six banks providing forecasts; by 2010, this number increased to eight banks for the median country.

I use two variables from this source to capture countries' repayment ability: the real GDP growth forecast (hereafter, GDP forecast) and the ten-year sovereign bond yield forecast (hereafter, sovereign bond yield forecast). The GDP forecast is the most frequently reported variable in the Consensus Economics survey, with over 25,000 observations for the Eurozone area (53,000 observations in the whole sample). Although the sovereign bond yield is less commonly reported, there are still more than 16,000 observations for the Eurozone area (35,000 observations in the whole sample). Notably, it is rare for an institution to report a forecast for any macroeconomic variable without also providing a GDP forecast (this occurs in fewer than two percent of observations). Consensus Economics provides each variable for two different time horizons. I use the GDP forecast by the end of the current year, $GDP^{f}_{b,y,t,c}$, and the following year, $GDP^{f}_{b,y',t,c}$, and the sovereign bond yield twelve months ahead, $Yield^{f}_{b,t+12,t,c}$.[9] Since this study focuses on lenders' behavior during the Eurozone sovereign debt crisis, I consider only banks' expectations for countries that were part of the Eurozone during the crisis. Hence, the sample includes 101 banks that forecast at least one country in this region. Panel A of Table 1 shows summary statistics from this source. We observe a significant forecast heterogeneity across banks, which is the main heterogeneity I exploit in the empirical analyses.

To analyze banks' sovereign bond decisions, I take advantage of the banks' debt holding data (EBA), which provides systematic data on the bank's balance sheets semi-annually since 2010.[10] Since the data is collected to make bank stress test, EBA presents a good cover of the bank's sovereign bonds holdings. In addition, it also provides information for different time maturities which go from 3 months to 15 years. I use two variables from this source: the banks' sovereign bond holdings from country c, $Bonds_{b,q,c}$ and the banks' total assets from country c, $Assets_{b,q,c}$.

Following (De Marco et al., 2021) approach, I merge the Consensus Economic survey data set with banks' debt holding data (EBA).[11] I match the bond holding of 77 banks with assets from Eurozone countries. After the matching process, in the sample, 45 banks (58 percent) hold bonds from the Eurozone core, 16 banks (21 percent) hold bonds from the Eurozone periphery, and 16 banks (21 percent) hold bonds from countries in both regions. The percentage difference is not surprising since the Eurozone core is larger in terms of countries and the sovereign debt market.

[9] In addition Consensus Economics reports the sovereign bond yield forecast three months ahead.
[10] Even when it is semiannual, they do not always report in the same quarter of the year.
[11] See Appendix 1 for more details.

Table 1 panel b shows summary statistics from all the banks in EBA, which I am able to match with Consensus Economics and assign an imprecision measure. Since the sample only contains global banks, the average bank in the sample holds a large amount of sovereign bonds: 16 Billions, to put in perspective this represents over 5 percent of Greek sovereign bond debt when the crisis started in 2009.

The change in banks' sovereign debt holding is a crucial variable to understanding the countries' debt rollover pressure a country suffers during a crisis. Unfortunately, this data has two important limitations: banks report in a semiannual fashion, and the data is available since 2010. Therefore, I complement the analysis with the syndicated loan market, which presents higher frequency data (monthly) and for a longer period (since 1991). LPC Dealscan provides detailed information on the syndicate loans. Each syndicated loan consists of a deal with different facilities. The interest rates are available at the facility level. I analyze the relative change in interest rates across banks' imprecision measure during the crisis.

To this end, I merged LPC Dealscan with Consensus Economics by linking the leader of the deal from LPC Dealscan with its forecast in Consensus Economics.[12] The process allows me to link around four thousand loans with bank forecast data in the Eurozone between 1991 and 2021. Table 1 panel c shows the summarize statistics for loans I am able to match with consensus Economics, the variable reported are: the total deal amount, $Amount_{b,t,f,c}$, the margins banks charge over the reference interest rate, $Margin_{b,t,f,c}$, and the spread they pay for the amount of money they decide to draw from the facility, $Spread_{b,t,f,c}$.

Finally, I compute the difference between banks' GDP forecasts and the actual variable realizations to build up banks' forecast errors and classify banks according to their precision. I obtained the actual GDP realization from the World Bank. In addition, I obtained the Greek sovereign bond yield from the European Central Bank (ECB).

[12] I follow the same procedure as De Marco and Friedheim (2024). I linked both databases through the name in each database. See Appendix 1.b for more details on the merge process between these two databases.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Obs.	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Panel A: Consensus Economics Survey								
Whole Sample								
$GDP^f_{b,y,t,c}$	1.3	2.1	25,402	-0.8	0.8	1.6	2.5	3.3
$GDP^f_{b,y',t,c}$	1.9	1.2	25,049	0.6	1.3	1.9	2.6	3.2
$Yield^f_{b,t+12,t,c}$	4.5	2.4	16,436	1.0	3.3	4.5	5.8	7.5
During the Crisis								
$GDP^f_{b,y,t,c}$	0.5	2.2	2,202	-3.3	-0.3	1.0	1.9	3.0
$GDP^f_{b,y',t,c}$	1.2	0.9	2,184	0.0	0.8	1.4	1.8	2.1
$Yield^f_{b,t+12,t,c}$	3.6	0.9	1,302	2.5	3.0	3.6	4.1	4.8
Eurozone Periphery								
$GDP^f_{b,y,t,c}$	1.3	2.6	8,783	-1.9	0.5	1.5	2.8	3.9
$GDP^f_{b,y',t,c}$	2.0	1.5	8,686	0.3	1.0	1.9	2.8	3.6
$Yield^f_{b,t+12,t,c}$	5.1	2.6	3,969	2.2	3.9	4.7	5.6	10.0
Eurozone Core								
$GDP^f_{b,y,t,c}$	1.4	1.8	16,619	0.0	0.9	1.6	2.4	3.0
$GDP^f_{b,y',t,c}$	1.9	1.0	16,363	0.9	1.3	1.8	2.5	3.0
$Yield^f_{b,t+12,t,c}$	4.3	2.3	12,467	0.9	2.8	4.5	5.9	7.4
Panel B: EBA Matched with Consensus Economics Amount								
	Mean	Std. Dev.	Obs.	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Whole Sample								
$Assets_{b,q,c}$	22.7	19.4	313	0.4	5.5	19.8	32.5	51.3
$Bonds_{b,q,c}$	16.2	14.4	286	0.2	5.0	14.7	21.2	37.4
During the Crisis								
$Assets_{b,q,c}$	16.6	15.7	182	0.1	1.7	14.7	27.1	42.9
$Bonds_{b,q,c}$	12.6	12.1	145	0.1	1.8	11.0	18.7	29.3
Eurozone Periphery								
$Assets_{b,q,c}$	26.4	25.8	102	0.1	1.4	17.3	51.3	65.1
$Bonds_{b,q,c}$	20.3	19.7	94	0.0	1.5	16.7	34.9	48.5
Eurozone Core								
$Assets_{b,q,c}$	21.0	15.1	211	1.2	11.5	20.1	28.7	37.0
$Bonds_{b,q,c}$	14.2	10.4	192	0.8	7.3	13.6	19.8	23.0
Panel C: LPC DealScan Matched with Consensus Economics Amount								
	Mean	Std. Dev.	Obs.	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Whole Sample								
$Amount_{b,t,f,c}$	5.7	14.9	2,621	0.1	0.3	1.2	4.4	13.2
$Margin_{b,t,f,c}$	190.7	141.3	846	40.0	75.0	150.8	275.0	395.0
$Spread_{b,t,f,c}$	190.0	139.6	846	40.0	75.0	150.8	275.0	383.3
During the Crisis								
$Amount_{b,t,f,c}$	6.5	14.4	290	0.1	0.3	1.1	4.9	18.3
$Margin_{b,t,f,c}$	275.6	136.4	78	110.0	175.0	275.0	350.0	450.0
$Spread_{b,t,f,c}$	275.3	135.2	78	110.0	175.0	275.0	350.0	450.0
Eurozone Periphery								
$Amount_{b,t,f,c}$	6.2	17.7	963	0.1	0.3	0.9	4.1	13.2

2.2 Imprecision Measure Definition

The imprecision measure ($Imp_{b,c}$) is the average square forecast error of bank b forecasting country c's GDP at the end of the current and following year,

$$Imp_{b,c} = \frac{\sum_t \left[(GDP_{y,c} - GDP^f_{b,y,t,c})^2 + (GDP_{y',c} - GDP^f_{b,y',t,c})^2 \right]}{\#Bank\,Forecasts}, \tag{1}$$

where $GDP_{y,c}$ and $GDP_{y',c}$ are the actual GDPs for country c at the end of the current year, y, and the following one, y', respectively; $GDP^f_{b,y,t,c}$ and $GDP^f_{b,y',t,c}$ are the bank b at period t GDP forecast for country c by the end of the current year and the following one, respectively; $\#Bank\,Forecasts$ is the number of forecasts during the sample period. $Imp_{b,c}$ is constructed using data between October 1989 and December 2008.[13]

The indicator provides a continuous measure of a banks' forecast imprecision. The imprecision measure is specific to each bank-country pair. For example, bank A could be more precise in forecasting Spain but less precise in forecasting Germany. To simplify interpretation, the indicator is normalized so that one unit represents a standard deviation at the country level. Additionally, $Imp_{b,c}$ is winsorized at the 1st and 99th percentiles to reduce the influence of outliers.

The imprecision measure is based on forecasts of countries' GDP across two different horizons, reflecting the assumption that banks value both forecast horizons equally. In this line, Consensus Economics also evaluates forecaster precision using GDP forecasts for both the end of the current and following year.[14] Appendix 1 shows how the indicator changes when only one of the forecast horizons is considered.

2.3 Imprecision Measure Descriptive Statistics

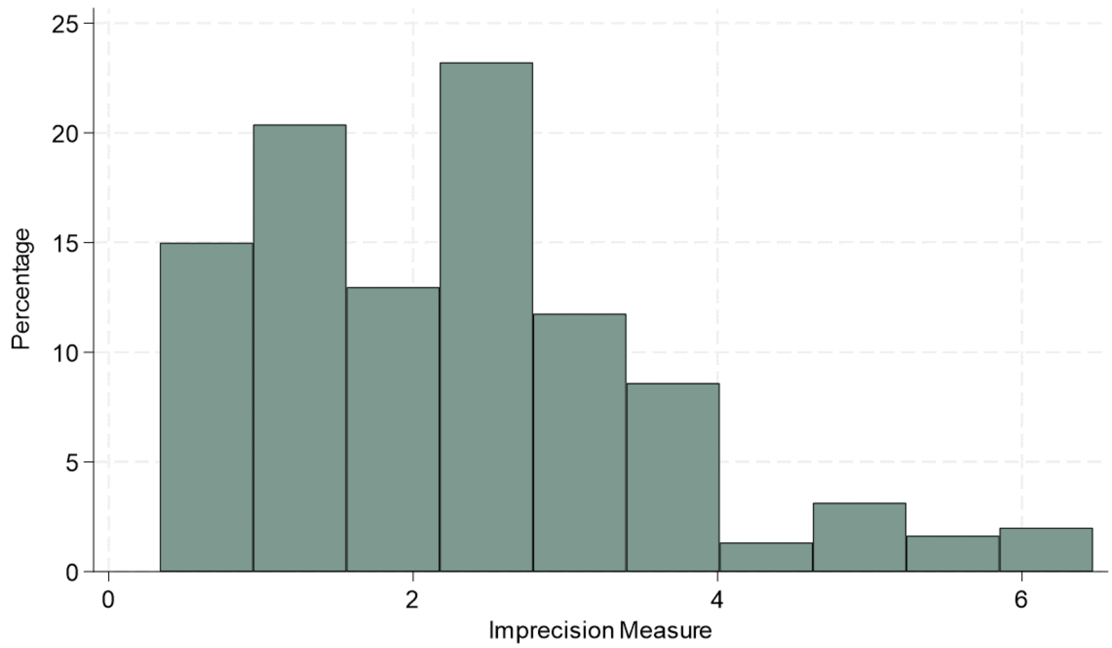
Banks presents a sizable dispersion in their GDP forecast errors before the crisis. Figure 2 shows the histogram of the imprecision measure. We observe significant variability in this measure, ranging from a bit above zero to around six.

The heterogeneity observed in Figure 2 is not driven by systematic differences in bank-level GDP forecasts. The average bank-country GDP forecast remains relatively constant across banks'

[13]I exclude the forecast made during 2009 to mitigate concerns about anticipation effects

[14]Consensus Economics additionally considers inflation forecasts for both the current and following year to assess banks' precision.

Figure 2: Imprecision Measure's Histogram



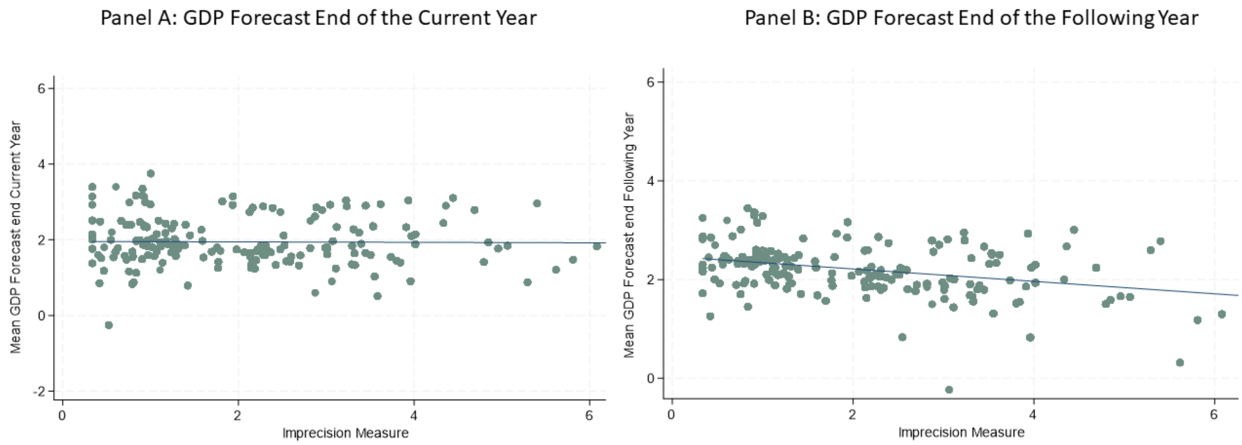
Note: This figure presents the histogram of the imprecision measure. The horizontal axis represents the imprecision measure, and the vertical axis is the percentage of banks in each bin. The sample consists of banks forecasting the Eurozone. Source own elaboration based on Consensus Economics.

imprecision measure. Figure 3 shows the average bank GDP forecast on the vertical axis and the imprecision measure on the horizontal axis; panel A shows the average forecast by the end of the current year and panel B by the end of the following year. There is virtually no correlation between the imprecision measure and the banks' average forecasts. Thus, it was not the case that less precise banks forecasted higher GDP for the Eurozone periphery before the crisis—a factor that could have led to their classification as more imprecise and driven greater forecast adjustments during the crisis.

The ranking of bank forecast precision has remained relatively stable over time; hence, there is a high correlation for the imprecision measure across different sample periods. Figure 4 shows that the banks' imprecision measure correlation with an alternative imprecision meausre which is constructed using the whole sample period, excluding the COVID pandemic. Appendix 1 shows that the imprecision measure is similar using other sample periods too.

The imprecision measure correlates with banks' observable characteristics. Figure 5 shows

Figure 3: Average Forecast Before the Crisis Period Across Banks' Imprecision Measure



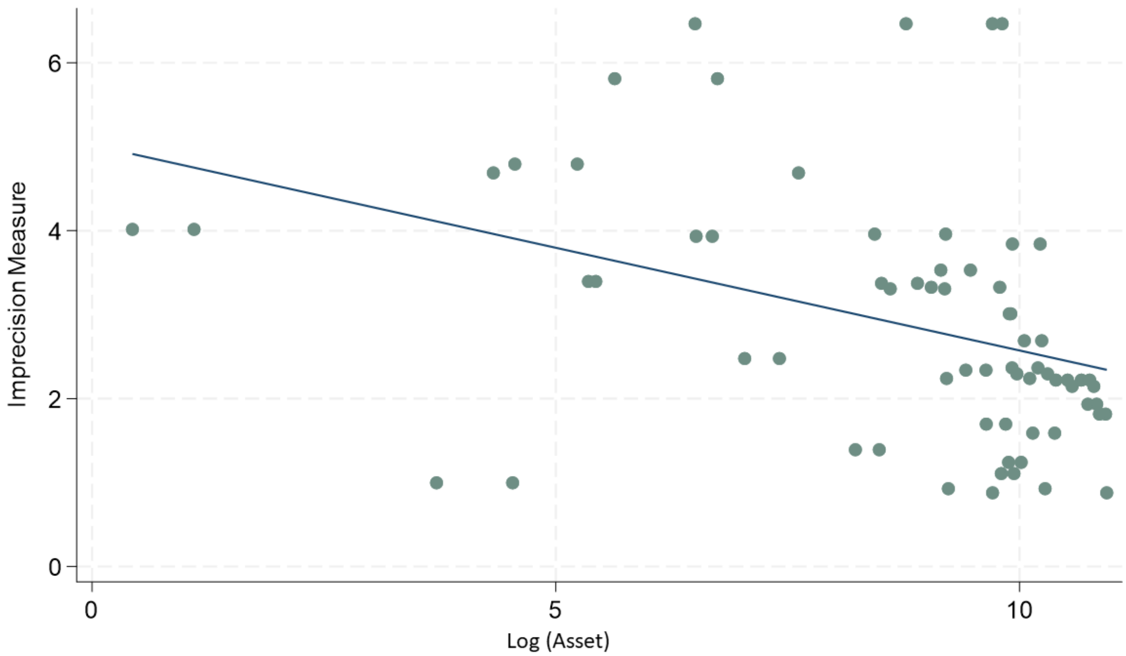
Note: This Figure shows the correlation between the bank GDP forecast before the crisis and the imprecision measure. The horizontal axis represents the bank-country imprecision measure. The vertical axis represents the GDP forecast by the end of the year (on the left) and by the end of the following year (on the right).

Figure 4: Imprecision Measure Stability Over Time

Note: This figure shows the correlation between the imprecision measure, and an alternative imprecision measure using data from October 1989 until the COVID Pandemic, December 2019.

that bank b imprecision measure for country c is negatively correlated with the logarithmic of total assets that bank b holds from country c, $log(Assets_{b,c})$ in 2010.[15] It is worth noting that Consensus Economics provides forecasts from the largest banks in the market; therefore, even the relatively smaller banks in this sample are among the largest banks in the world.

Figure 5: Correlation Between Bank Total Assets and the Imprecision Measure



Note: This figure shows the correlation between the bank's total assets and its imprecision measure. The horizontal axis represents the imprecision measure, and the vertical axis represents the banks' total assets in 2010. The sample is Eurozone countries. The source is own elaboration based on Consensus Economics and EBA.

Banks with headquarters in the country they are forecasting tend to be less imprecise about that country. This effect is not completely driven by banks' home bias; while the percentage share of assets (rather than the total amount) has a negative correlation with the imprecision measure, this relationship is not statistically significant.

Table 2 summarizes these correlations. It displays the regression of the imprecision measure on the logarithm of bank b's total assets from country c, $log(Assets_{b,c})$, a dummy variable equal to one if bank b is headquartered in the country it is forecasting, $Local_{b,c}$, and bank b's share of

[15] I consider the level of assets in 2010, the first period with data from EBA. Other regularities have been documented; for instance, (De Marco et al., 2021) shows that banks' precision about one country correlates with the bank portfolio share of this country.

assets from country c, $Share_{b,c}$. All regressions yield negative coefficients, but only the first two are statistically significant.

Table 2: Imprecision Measure and Bank Observable Characteristics

	(1)	(2)	(3)
	$Imp_{b,c}$	$Imp_{b,c}$	$Imp_{b,c}$
$log(Assets_{b,c,})$	-0.233**		
	(0.100)		
$Share_{b,c}$		-1.733	
		(1.085)	
$Local_{b,c}$			-1.020**
			(0.492)
R^2	0.141	0.070	0.118
Observations	68	68	68

Note: The table shows the correlation between the Imprecision Measure and bank b amount of assets from country c, $log(Assets_{b,c,})$, in column 1, its share of assets from country c, $Share_{b,c}$, in column 2, and if the bank has headquarter is the country is forecasting, $Local_{b,c}$, in column 3. Standard errors are clusterized at the bank country level.

There is a theoretical connection between imprecision and perceived correlation within a group. Several scholars point out that broader categories, like the Eurozone periphery, lead to less precise forecasts and a perception of higher correlation among assets within the category—such as between Greek GDP and that of other Eurozone periphery countries—compared to agents who use finer categories, such as treating each Eurozone periphery country separately (Jehiel, 2022; Spiegler, 2016; Bordalo et al., 2016, 2020). Section 5 and Appendix 5 present a model in line with (Bordalo et al., 2016) and present additional empirical evidence.

I test if this is the case for the subset of banks that forecast both Greek GDP and GDP for another Eurozone country. I regress bank b's GDP forecast for country c in period t on its own GDP forecast for Greece in the same period, including an interaction term between the Greek GDP forecast and the imprecision measure. I also include a bank-country fixed effect to control for time-invariant differences across banks and countries.

$$GDP^f_{b,y,t,c} = \beta_1 GDP^f_{b,t,Gr} + \beta_2 GDP^f_{b,t,Gr} \times Imp_{b,c} + \omega_{b,c} + \epsilon_{b,t,c}.$$

Table 3 presents this specification for the entire sample period up to the COVID pandemic.[16] More imprecise banks exhibit a stronger GDP forecast correlation between Greece and other Eurozone periphery countries compared to more precise banks. This effect is not driven by the crisis

[16]Since Greece was incorporated into the sample in 2005, the sample period starts in that year.

period; Appendix 1 shows that, even after the crisis, more imprecise banks continue to exhibit a stronger correlation than less imprecise ones.

Regressing bank b's GDP forecast for a Eurozone core country on its own GDP forecast for Greece, there is virtually no difference across banks imprecision measure, as shown in Table 4. If anything, more imprecise banks exhibit a slightly lower correlation than more precise banks.

Section 3 shows that more imprecise banks changed their forecasts against the Eurozone periphery during the crisis. Section 4 shows that more imprecise banks shifted their portfolio away from the Eurozone periphery to a larger extent. The main rationalization for these empirical findings is that more imprecise banks perceive a larger correlation between Greece and the rest of the Eurozone periphery. Section 5 discusses in more detail this interpretation of the empirical findings.

Table 3: Bank GDP Forecast Correlation Between Greece and Eurozone Periphery

	(1) $GDP^f_{b,y,t,c}$	(2) $GDP^f_{b,y,t,c}$	(3) $GDP^f_{b,y',t,c}$	(4) $GDP^f_{b,y',t,c}$
$GDP^f_{b,y,t,Gr}$	0.318***	0.211***		
	(0.039)	(0.061)		
$GDP^f_{b,y,t,Gr} \times Imp_{b,c}$		0.040**		
		(0.012)		
$GDP^f_{b,y',t,Gr}$			0.309***	0.171*
			(0.049)	(0.083)
$GDP^f_{b,y',t,Gr} \times Imp_{b,c}$				0.051*
				(0.024)
Country-Bank FE	Yes	Yes	Yes	Yes
R^2	0.476	0.485	0.433	0.443
Observations	612	612	612	612

Note: This table shows the bank GDP forecast correlation between Greece, $GDP^f_{b,t,Gr'}$, and the rest of the EU periphery countries, $GDP^f_{b,y,t,c}$. Where $Imp_{b,c}$ is the imprecision measure. Sample period: February 2005- December 2019. Standard errors are clusterized at the bank country level.

3 Heterogeneous Banks' Forecasts During the Crisis

This section shows that banks with less precise forecasts before the crisis adjusted their GDP forecasts downward and their sovereign bond yield forecasts upward for the Eurozone periphery (excluding Greece) more than more precise banks. I find virtually no significant differences in forecast adjustments for Eurozone core countries across banks' imprecision measure. For expo-

Table 4: Bank GDP Forecast Correlation Between Greece and Eurozone Core

	(1) $GDP^f_{b,y,t,c}$	(2) $GDP^f_{b,y,t,c}$	(3) $GDP^f_{b,y',t,c}$	(4) $GDP^f_{b,y',t,c}$
$GDP^f_{b,y,t,Gr}$	0.137***	0.172***		
	(0.025)	(0.049)		
$GDP^f_{b,y,t,Gr} \times Imp_{b,c}$		-0.011		
		(0.019)		
$GDP^f_{b,y',t,Gr}$			0.188***	0.218**
			(0.036)	(0.086)
$GDP^f_{b,y',t,Gr} \times Imp_{b,c}$				-0.010
				(0.023)
Country-Bank FE	Yes	Yes	Yes	Yes
R^2	0.150	0.151	0.257	0.258
Observations	1328	1328	1327	1327

Note: This table shows the bank GDP forecast correlation between Greece, $GDP^f_{b,t,Gr'}$, and the EU core countries, $GDP^f_{b,y,t,c}$. Where $Imp_{b,c}$ is the imprecision measure. Sample period: February 2005- December 2019. Standard errors are clusterized at the bank country level.

sition reasons, I focus here on GDP forecasts by the end of the current year. Appendix 2 shows similar results for the GDP forecast by the end of the following year.

3.1 Bank Forecasts for the Eurozone Periphery During the Crisis

I consider two crisis' indicators. The first is a dummy variable, $crisis_t$, which equals one from October 2009 to June 2012, and zero otherwise. October 2009 marks the election of a new government in Greece and the beginning of rumors about fiscal statistics manipulation, which I consider the starting point of the crisis. June 2012 is the previous month to Draghi's "whatever it takes" announcement, marking the end of the crisis. The second crisis indicator is the Greek sovereign bond yield at the end of the month prior to each forecast, $Yield_{Gr,t-1}$, which reflects market perceptions of the crisis's severity. Appendix 2 presents alternative crisis definitions, yielding similar results.[17]

I perform two specifications. In the first one, I regress banks' GDP and sovereign bond yield forecasts on the interaction between the imprecision measure ($Imp_{b,c}$) and the crisis dummy ($crisis_t$). In the second, the key variable of interest is the interaction between $Imp_{b,c}$ and $Yield_{Gr,t-1}$. Both

[17] As robustness checks, I also consider two alternative starting points: January 2010, when Greece began negotiations with the IMF, and May 2010, when it received its first IMF Stand-By agreement. Another potential endpoint is December 2013, when European economies began to recover pre-crisis production levels.

specifications include bank-country and country-month fixed effects, controlling for time-invariant bank characteristics, such as $Imp_{b,c}$, and monthly country-level shocks, such as $Yield_{Gr,t-1}$ or $Crisis_t$.

$$y^f_{b,t,c} = \beta_1 Imp_{b,c} \times Crisis_t + \omega_{b,c} + \omega_{t,c} + \epsilon_{b,t,c}, \tag{2}$$

$$y^f_{b,t,c} = \beta_1 Imp_{b,c} \times Yield_{Gr,t-1} + \omega_{b,c} + \omega_{t,c} + \epsilon_{b,t,c}, \tag{3}$$

where $y^f_{b,t,c}$ represents the GDP forecast by the end of the current year, $GDP^f_{b,y,t,c}$, or the twelve-month-ahead sovereign bond yield forecast, $Yield^f_{b,t+12,t,c}$, in period t for country c by bank b. $\omega_{b,c}$ and $\omega_{t,c}$ are bank-country and time-country fixed effects, respectively.

Table 5 presents estimates for equations 2 and 3 from January 2008 to June 2012. The first two columns show the main coefficient of interest for equation 2, while the last two columns present results for equation 3. In columns 1 and 3, the dependent variable is $GDP^f_{b,y,t,c}$, and in columns 2 and 4, it is $Yield^f_{b,t+12,t,c}$.

Table 5: Bank Forecast Heterogeneity and the Greek Crisis

	(1)	(2)	(3)	(4)
	$GDP^f_{b,y,t,c}$	$Yield_{b,t+12,t,c}$	$GDP^f_{b,y,t,c}$	$Yield_{b,t+12,t,c}$
$Imp_{b,c} \times Crisis_t$	-0.122***	0.123**		
	(0.038)	(0.060)		
$Imp_{b,c} \times Yield_{Gr,t-1}$			-0.049*	0.065*
			(0.026)	(0.034)
Mean Forecast	-0.49	4.43	-0.49	4.43
Country-Month FE	Yes	Yes	Yes	Yes
Country-Bank FE	Yes	Yes	Yes	Yes
R^2	0.983	0.699	0.983	0.702
Observations	819	504	815	504

Note: This table reports estimates for equations 2 and 3. In columns 1 and 3, the dependent variable is bank b's GDP forecast for the end of year t for country c, $GDP^f_{b,y,t,c}$; in columns 2 and 4, it is the twelve-month-ahead sovereign bond yield forecast, $Yield^f_{b,t+12,t,c}$. Sample period: January 2008–June 2012, for the Eurozone periphery excluding Greece. Standard errors, clustered at the bank-country-crisis level, are reported in parentheses.

In the first two columns, we observe that one standard deviation more imprecise bank reduced its GDP forecast for the Eurozone periphery, excluding Greece, by 0.122 more than the average bank and increased its sovereign bond yield forecast by 0.123 more than the average bank. These results are sadistically significant and economically meaningful; one standard deviation more imprecise bank reduced its GDP forecast by an additional 25 percent with respect to the average forecaster and increased its sovereign bond yield forecast by an additional 2.5 percent with respect to the average forecaster. Table 5 presents similar results considering the severity of the crisis. In the last two columns, the coefficient is positive and significant for $Yield^f_{b,t+12,t,c}$ and negative for $GDP^f_{b,y,t,c}$, as expected.

The results are robust to banks having different reactions to local news. I re-estimate equations 2 and 3 with an additional control: the interaction between the imprecision measure and the local sovereign bond yield, which accounts for potential concerns that less precise banks' forecasts may react more to local news than the more precise banks. This control mitigates the concern that the correlation between the Greek sovereign bond yield and local yields drives results.

Table 6 shows that after including this control, the coefficients remain similar to those in Table 5. We find that less precise banks adjust their GDP and sovereign bond yield forecast almost in the same magnitude as in the previous specifications. The interaction between the local sovereign bond yield and the imprecision measure is not statistically significant in all specifications.

Table 6: Bank Forecast Heterogeneity Controlling for Local Sovereign Bond Yield

	(1) $GDP^f_{b,y',t,c}$	(2) $Yield_{b,t+12,t,c}$	(3) $GDP^f_{b,y',t,c}$	(4) $Yield_{b,t+12,t,c}$
$Imp_{b,c} \times Crisis_t$	-0.110***	0.104*		
	(0.040)	(0.060)		
$Imp_{b,c} \times Yield_{Gr,t-1}$			-0.057**	0.080*
			(0.023)	(0.043)
$Imp_{b,c} \times Yield_{c,t-1}$	-0.029	0.044	0.017	-0.029
	(0.039)	(0.047)	(0.029)	(0.054)
Mean Forecast	-0.49	4.43	-0.49	4.43
Country-Month FE	Yes	Yes	Yes	Yes
Country-Bank FE	Yes	Yes	Yes	Yes
R^2	0.983	0.701	0.983	0.703
Observations	815	504	815	504

Note: This table reports estimates for equations 2 and 3, including as a control the interaction between the imprecision measure and the local sovereign bond yield. In columns 1 and 3, the dependent variable is bank b's GDP forecast for the end of year t for country c, $GDP^f_{b,y,t,c}$; in columns 2 and 4, it is the twelve-month-ahead sovereign bond yield forecast, $Yield^f_{b,t+12,t,c}$. Sample period: January 2008–June 2012, for the Eurozone periphery excluding Greece. Standard errors, clustered at the bank-country-crisis level, are reported in parentheses.

3.2 Bank Forecasts for the Eurozone Core During the Crisis

This subsection repeats the previous analyses for the Eurozone core countries as a robustness check. I estimate the specifications from Table 6 for the sample of Eurozone core countries. Table 7 shows that in almost all specifications, the coefficients of interest are not statistically significant. The only exception is the last column, where $Yield^f_{b,t+12,t,c}$ is the dependent variable, and the coefficient of interest is the interaction between $Imp_{b,c}$ and $Yield_{Gr,t-1}$. However, the coefficient is negative; hence, if anything, less precise banks expected a reduction in the Eurozone core sovereign bond yields compared to more precise banks during the crisis.

Table 7: Eurozone Core

	(1)	(2)	(3)	(4)
	$GDP^f_{b,y,t,c}$	$Yield_{b,t+12,t,c}$	$GDP^f_{b,y,t,c}$	$Yield_{b,t+12,t,c}$
$Imp_{b,c} \times Crisis_t$	0.026	0.001		
	(0.032)	(0.040)		
$Imp_{b,c} \times Yield_{Gr,t-1}$			0.014	-0.058***
			(0.015)	(0.019)
$Imp_{b,c} \times Yield_{c,t-1}$	0.012	0.041	0.016	-0.027
	(0.018)	(0.025)	(0.018)	(0.023)
Country-Month FE	Yes	Yes	Yes	Yes
Country-Bank FE	Yes	Yes	Yes	Yes
R^2	0.984	0.817	0.984	0.821
Observations	2065	1710	2065	1710

Note: This table reports the estimation of equations 2 and 3. In columns 1 and 3, the dependent variable is bank b's GDP forecast for the end of the year in period t for country c, $GDP^f_{b,y,t,c}$, and in columns 2 and 4, it is the sovereign yield forecast one year ahead for country c, $Yield^f_{b,t+12,t,c}$. Sample period: January 2008–June 2012 for Eurozone core countries. Standard errors are reported in parentheses and are clustered at the bank-country-crisis level.

This section shows that more imprecise lenders adjusted their forecasts for the Eurozone periphery more than the more precise lenders during the crisis. These results hold across various controls, including country-month and bank-country fixed effects. Additionally, I find virtually no significant differences in banks' imprecision measures when forecasting the Eurozone core during the crisis period. Appendix 2 presents additional results, including dynamic differences-in-differences, alternative time horizons for the dependent variable, different crisis periodizations, and alternative imprecision measures. These results are consistent with those reported here.

4 Changes in Banks' Portfolios

Going back to the Eurozone periphery, this section provides evidence that less precise lenders shifted their portfolio away from the Eurozone periphery by relatively more. The first subsection focuses on the sovereign bonds market, while the second presents complementary evidence from the syndicated loan market.

4.1 Sovereign bonds Market

This subsection analyzes banks' sovereign bond portfolio reallocation during the Greek crisis. The main variable of interest is the total bond holdings by bank b from country c in quarter q, $Bonds_{b,q,c}$.[18] I define $\log(Bonds_{b,q,c})$ as the logarithm of $Bonds_{b,q,c}$.[19]

As the Greek sovereign bond yield increased, banks reduced their sovereign bond portfolio holdings from the rest of the Eurozone periphery. Figure 6 presents a binscatter plot representing the following regression:

$$\log\left(Bonds_{b,q,c}\right) = \beta_1 Yield_{Gr,q-1} + \omega_{b,c} + \epsilon_{b,q,c},$$

Where $Yield_{Gr,q-1}$ is the Greek yield at the end of the previous quarter, $\omega_{q,c}$ is a country-quarter fixed effect.

I repeat the same specification, breaking down the sample between less precise banks (above the median imprecision measure) and more precise banks (below the median imprecision measure). Figure 7 shows that less precise banks drove the portfolio shift away from the Eurozone periphery during the crisis.

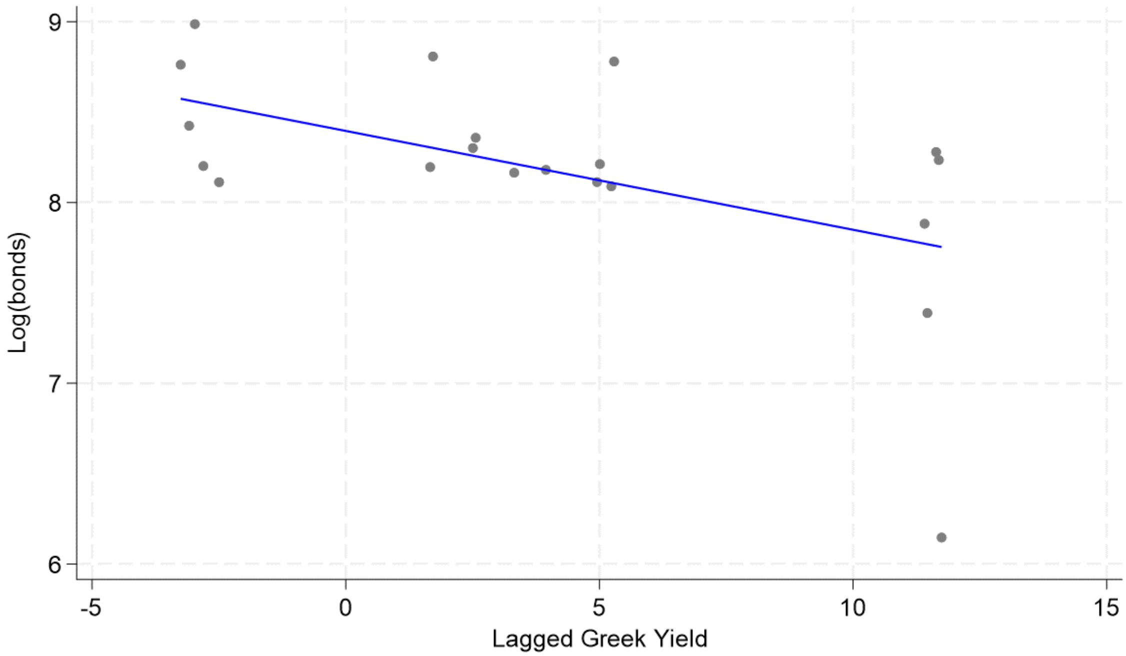
Figure 8 presents the same binscatter plot for banks' sovereign debt holdings from Eurozone core countries. Consistent with the evidence from the previous section, we do not observe significant differences across banks' imprecision in their portfolio decisions for Eurozone core countries during the crisis.

Regressing the $\log(Bonds_{b,q,c})$ on the interaction between the continues measure of imprecision $(Imp_{b,c})$ and ,$Yield_{Gr,q-1}$ I find similar results,

[18] Note that EBA reports banks' portfolios at the end of two different quarters per year.

[19] Since EBA began systematically reporting $Bonds_{b,q,c}$ in 2010, we cannot compare the pre-crisis and crisis periods.

Figure 6: Bank Portfolio holdings During the Crisis Eurozone Periphery



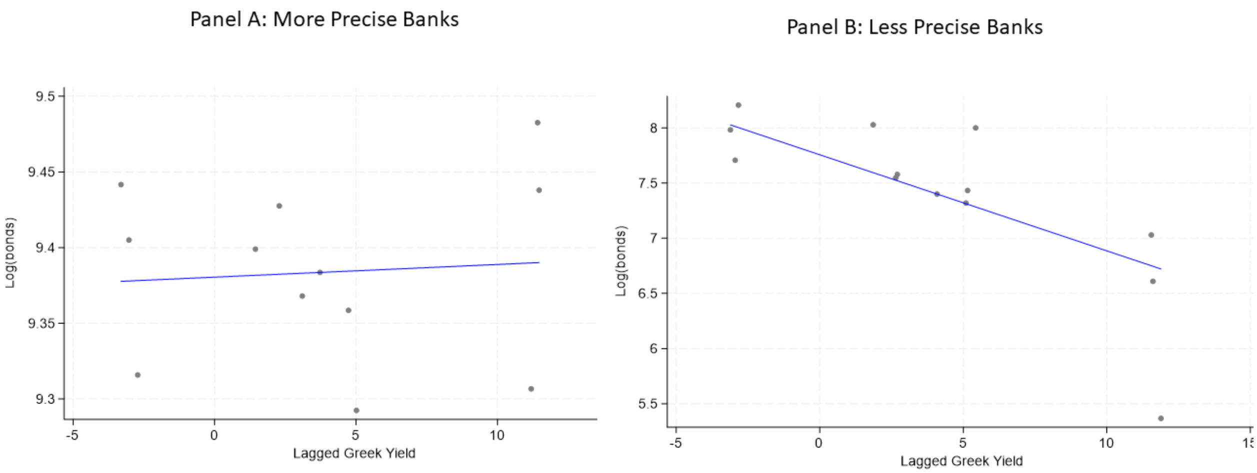
Note: Binscatter: each point represents six observations. The horizontal axis represents the average Greek sovereign bond yield in the previous quarter, and the vertical axis represents the country's sovereign bond in bank b's balance sheet. Sample period: Q1-2010 to Q2-2012. Eurozone periphery excluding Greece.

$$\log(Bonds_{b,q,c}) = \beta_1 Imp_{b,c} \times Peri_c \times Yield_{Gr,q-1} + \beta_2 Imp_{b,c} \times Core_c \times Yield_{Gr,q-1} + Imp_{b,c} \times Yield_{c,q-1} + \omega_{b,c} + \omega_{q,c} + \epsilon_{b,q,c}, \tag{4}$$

where $Peri_c$ is a dummy variable equal to one if country c is part of the Eurozone periphery, and zero otherwise, $Core_c$ is a dummy variable equal to one if country c is part of the Eurozone core and zero otherwise, and $\omega_{b,c}$ is a country-bank fixed effect. The parameters of interest are β_1 and β_2, which capture the interaction between the imprecision measure, $Imp_{b,c}$, the Greek sovereign bond yield $Yield_{Gr,q-1}$, and the regional dummies $Peri_c$ and $Core_c$, respectively.

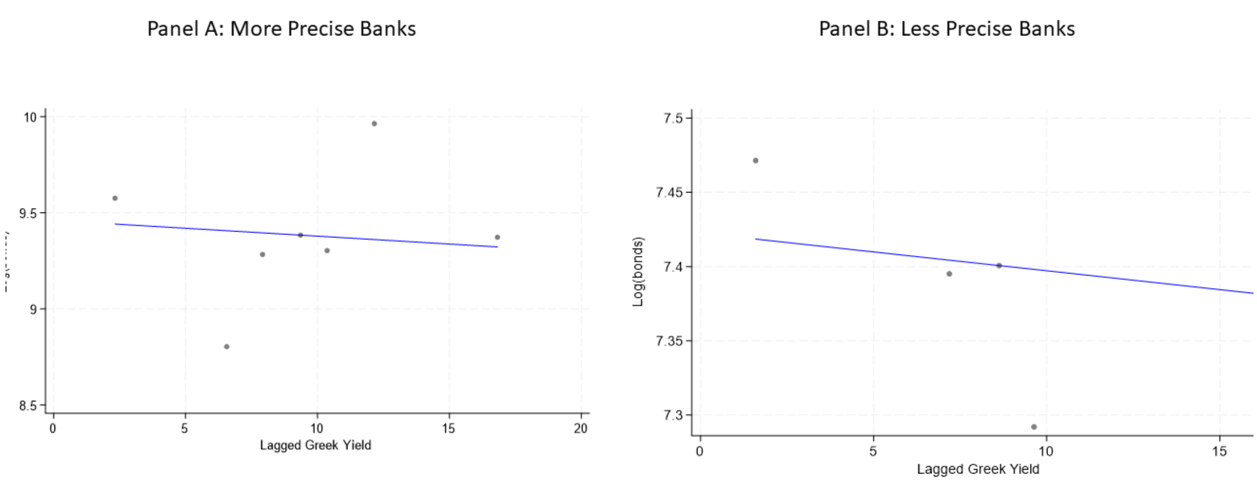
Table 8 presents the results for equation 4 during the crisis period. Column 1 controls for bank-country fixed effects and $Yield_{Gr,q-1}$, column 2 includes bank-country and quarter fixed effects, and column 3 includes bank-country and country-quarter fixed effects, and column 4 presents the

Figure 7: Bank Portfolio holdings from Eurozone Periphery Imprecise and Precise Banks



Note: Binscatter: each point represents six observations. The horizontal axis represents the average Greek sovereign bond yield in the previous quarter, and the vertical axis represents the country's sovereign bond in bank b's balance sheet. Sample period: Q1-2010 to Q2-2012. Eurozone periphery excluding Greece.

Figure 8: Bank Portfolio from Eurozone Core Imprecise and Precise Banks



Note: Binscatter: each point represents six observations. The horizontal axis represents the average Greek sovereign bond yield in the previous quarter, and the vertical axis represents the country's sovereign bond in the bank b's balance sheet. Sample period: Q1-2010 to Q2-2012. Eurozone core.

main specification (equation 4), which includes bank-country and country-quarter fixed effects and the interaction between the imprecision measure and the local sovereign bond yield. All specifications present a significant and negative coefficient for the Eurozone periphery and a non-significant coefficient for the Eurozone core.

Table 8: Change in Banks' Portfolio During the Crisis

	$\log\left(Bonds_{b,q,c}\right)$	$\log\left(Bonds_{b,q,c}\right)$	$\log\left(Bonds_{b,q,c}\right)$	$\log\left(Bonds_{b,q,c}\right)$
$Imp_{b,c} \times Peri_c \times Yield_{Gr,q-1}$	-0.009*	-0.009*	-0.019***	-0.022***
	(0.005)	(0.005)	(0.005)	(0.007)
$Imp_{b,c} \times Core_c \times Yield_{Gr,q-1}$	0.003	0.003	-0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)
$Imp_{b,c} \times Yield_{c,q-1}$				0.041
				(0.060)
Bank-country FE	Yes	Yes	Yes	Yes
$Yield_{Gr,q-1}$	Yes	-	-	-
Quarter FE	No	Yes	-	-
Country-quarter FE	No	No	Yes	Yes
R^2	0.988	0.988	0.991	0.992
Observations	123	123	115	115

Note: This table reports the estimation of equation 4. The dependent variable is the logarithm of bank sovereign bond holdings. Sample period: Q2-2010 to Q2-2012. Eurozone periphery excluding Greece. Standard errors, clustered at the bank-country level, are reported in parentheses.

Unfortunately, Banks' sovereign bond holding data is available since 2010, so it is not possible to make the same analyzes as with expectation data, in addition the low data frequency may hide banks' portfolio movements. To address these concerns, the following subsection presents additional evidence from the syndicated loan market, where data are available monthly and cover the period before the Greek crisis.

4.2 Syndicated Loan Market

Lenders expecting a higher sovereign bond yield and lower GDP growth for Eurozone periphery countries should charge higher interest rates on syndicated loans for firms headquartered in these countries. Intuitively, the interest rate a firm faces can be broken down into country risk plus the company's idiosyncratic risk (Hassan et al., 2021). After controlling for firm fixed effects, less precise banks should charge higher interest rates to companies from the Eurozone periphery during the crisis.

A syndicated loan (deal) typically includes different lines (facilities). Each facility includes different interest rates. One of the most common facilities in the sample is the term loan, which represents a fixed amount of money that bank b lends to firm f.[20] This facility includes two main interest rates: the margin charged by banks over the reference interest rate, $Margin$, and the spread charged on the amount drawn from the facility, $Spread$.

I regress the facility margin, $Margin_{b,t,f,c}$, and the spread drawn, $Spread_{b,t,f,c}$, on the interaction between the crisis dummy and the imprecision measure in equation 5, and on the interaction between the Greek sovereign bond yield at the end of the previous month and the imprecision measure in equation 6. Both specifications include firm fixed effects, ω_f, and year-country fixed effects, $\omega_{c,y}$.

$$i_{b,t,f,c} = \beta_1 Imp_{b,c} \times Crisis_t + \omega_{c,y} + \omega_f + \epsilon_{b,t,c,f}, \tag{5}$$

$$i_{b,t,f,c} = \beta Imp_{b,c} \times Yield_{Gr,t-1} + \omega_{c,y} + \omega_f + \epsilon_{b,t,c,f}, \tag{6}$$

where $i_{b,t,f,c}$ represents $Margin_{b,t,f,c}$ or $Spread_{b,t,f,c}$, depending on the specification.

Equations 5 and 6 follow a similar structure to the analysis of banks' forecasts, though with some important differences. Here, I include firm fixed effects to control for firm-specific idiosyncratic risk. By including firm fixed effects, I focus on firms that received at least two loans during the analysis period. To maximize the sample, I extend the analysis period from January 2002 (when the Euro was implemented) to June 2012.[21] Additionally, I use country-year fixed effects instead of country-month fixed effects because, in some months, only one local firm in certain countries (e.g., Portugal) took out a syndicated loan.[22]

Table 9, in the first two columns, reports the results for specification 5, and the last two columns for specification 6. In all specifications, less precise banks charge higher $Margin$ and $Spread$ rates to companies in the Eurozone periphery compared to more precise banks. The coefficients are statistically significant in the first two columns but not in the last two.

The syndicated loan market results align with those observed in the bond market, showing

[20] Another common line is the credit line, which provides extra liquidity that a firm can draw on as needed, similar to a credit card for an individual.

[21] The median firm between 1990 and 2021 received nine syndicated loans, roughly one every three and a half years.

[22] Following standard procedures, I exclude firms in the financial, real estate, and insurance sectors (SIC codes 6000-6700) (De Marco, 2019). I also exclude loans that are amendments to existing loans, as these are often misreported in DealScan as new loans despite not necessarily involving new funds (Roberts, 2015). Finally, I remove loans with missing industry SIC codes, reducing the sample by around 7,000 observations.

Table 9: Change in Banks' Syndicated Loan Margins during the Crisis

	(1)	(2)	(3)	(4)
	$Margin_{b,c,t,f}$	$Spread_{b,c,t,f}$	$Margin_{b,c,t,f}$	$Spread_{b,c,t,f}$
$Imp_{b,c} \times Crisis_t$	54.395***	47.325***		
	(15.154)	(16.038)		
$Imp_{b,c} \times Yield_{Gr,t-1}$			1.403	0.035
			(1.851)	(1.069)
Country-Year FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
R^2	0.709	0.827	0.701	0.818
Observations	103	103	103	103

Note: This table reports the estimation of equations 5 and 6. The dependent variable is the term facility margin in columns 1 and 3, and the spread drawn in columns 2 and 4. The sample period is between January 2002 and June 2012, covering the Eurozone periphery (excluding Greece) and the Eurozone core. Standard errors, clustered at the bank-country level, are reported in parentheses.

that less precise lenders tend to increase the interest rates they charge to firms in the Eurozone periphery more than the more precise lenders.

5 Empirical Findings' Discussion

This section discusses two potential explanations for the empirical findings. The primary explanation is that some banks rely on broader categories, like the Eurozone periphery, leading to less precise forecasts and a perceived higher correlation within the category than banks with finer categories. When the former receive news about a country in the category, such as Greece, they adjust their expectations for other countries in the same category more significantly than banks who use finer categories that separate Greece from the rest of the Eurozone periphery. An alternative explanation is that more imprecise banks learn more during the crisis. In a Bayesian model with incomplete information, for example, less precise banks have more dispersed priors before the crisis; if the crisis is a signal with the same precision for all banks, those with less precise priors make larger forecast adjustments during the crisis. Appendix 5 discusses this model in more detail.

The primary explanation aligns with evidence from the empirical finance literature, which shows that institutional investors often use categories for organizational purposes, such as comparing traders' performance (Swensen, 2009). (Barberis and Shleifer, 2003) argue that categorization leads institutional investors to perceive asset price fundamentals within a category as more correlated than they actually are.[23] Appendix 5 presents a model in line with (Bordalo et al., 2012, 2016) that generates this pattern.[24] Such models have been used to explain both professional forecasters' overreactions to macroeconomic news (Bordalo et al., 2020) and extrapolation across financial cycles (Bordalo et al., 2018).

The standard approach to disentangle between these two explanations is to identify a variable in agents' information set that can predict their forecast errors, defined as the actual variable realization minus the agents' forecasts (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). In this context, I define the bank b GDP forecast error in period t about country c as $GDP\ FE_{b,t,c} = GDP_{y,c} - GDP^f_{b,y,t,c}$.

In this literature, agents' forecast revision measures new information in their information set at time t. The forecast revision is defined as the forecast in period t minus the forecast from period $t-1$ for the same variable. Here, I define bank b's GDP forecast revision for Greece as the difference between its forecast for Greek GDP by the end of the current year in period t and its forecast for Greek GDP by the end of the current year in period $t-1$, $GDP\ FR_{b,t,c} = GDP^f_{b,y,t,c} - GDP^f_{b,y,t-1,c}$.

Several scholars have shown that sophisticated investors often present a negative correlation between their forecast revisions and forecast errors (Bordalo et al., 2020, 2024b). This finding is usually interpreted as agents overreacting to new information, challenging models with Bayesian agents, and incomplete information. I test a related question: whether less precise banks exhibit a stronger negative correlation between their Greek GDP forecast revisions and their GDP forecast errors for the rest of the Eurozone periphery. I perform a regression similar to those in the literature, including an interaction term between the imprecision measure, $imp_{b,c}$, and the bank's forecast revision for Greece, $GDP\ FR_{b,t,Gr}$,

$$GDP\ FE_{b,t,c} = GDP\ FR_{b,t,Gr} + GDP\ FR_{b,t,Gr} \times imp_{b,c} + \epsilon_{b,t,c} \tag{7}$$

Table 10 presents the results of equation 7, with Eurozone periphery countries in column 1, including bank-country fixed effects in column 2. Columns 3 and 4 show the same specifications for Eurozone core countries, with column 4 also including bank-country fixed effects. Consistent

[23]This hypothesis has been used to explain excess asset price co-movement within categories (Barberis et al., 2005; Wahal and Yavuz, 2013; Drake et al., 2017; Ashour et al., 2023).

[24]Various micro-foundations explain why categorization may lead to extrapolation, including works by (Jehiel, 2005, 2022; Bordalo et al., 2023; Spiegler, 2016; Bordalo et al., 2018, 2019, 2012).

with the main hypothesis, we observe a negative coefficient for the interaction term in the first two columns and a positive, though not significant, coefficient in the last two columns.

Table 10 offers suggestive evidence supporting the main hypothesis. However, since only a subset of banks provides GDP forecasts for Greece and another Eurozone periphery country, this analysis includes fewer banks than previous specifications. Despite potential statistical power limitations, the coefficient of interest is significant in the first column and just below the 90 percent significance level in the second column. I find smaller coefficients with the opposite sign and no significance for the Eurozone core sub-sample.

Table 10: Banks' Forecast Errors

	EU Periphery		EU Core	
	$GDP\ FE_{b,y,t,c}$	$GDP\ FE_{b,y,t,c}$	$GDP\ FE_{b,y,t,c}$	$GDP\ FE_{b,y,t,c}$
$GDP\ FR_{b,t,Gr}$	0.106	0.103	-0.086	-0.091
	(0.127)	(0.162)	(0.151)	(0.169)
$GDP\ FR_{b,t,Gr} \times Imp_{b,c}$	-0.071*	-0.070	0.019	0.018
	(0.034)	(0.044)	(0.040)	(0.043)
Country-Bank FE	No	Yes	No	Yes
R^2	0.016	0.064	0.001	0.068
Observations	546	545	1189	1186

Note: This table presents the correlation between the bank's GDP forecast error, $GDP\ FE_{b,t,c}$, and its GDP forecast revision for Greece, $GDP\ FR_{b,t,Gr}$. The first two columns report results for the Eurozone periphery, while the last two columns focus on the Eurozone core. Sample period: January 2005 to December 2019. Forecast errors are clustered at the bank-country level.

6 Quantitative Model

This section proposes a relatively standard two-country endogenous default model to quantify the effect of less precise lenders on countries' default probabilities. There are a few new elements in this model. There is a common shock to both countries' endowments, which generates a positive correlation between them. I incorporate the empirical discussion assuming that lenders (wrongly) believe that the common shock has a larger weight on countries' endowment process, and so the correlation across endowments is larger.

Lenders have access to a signal about one country's future endowment. Given lenders' (wrong) beliefs, they update their beliefs about the second country more than what a Bayesian lender would do. In case the signal is negative, lenders would provide a worse price schedule for the second country's bond price, putting pressure on the second country's debt rollover and so increasing its default incentives. The main exercise consists of comparing this economy with another where lenders are Bayesian, which is the usual reference in the literature (Arellano, 2008; Paluszynski, 2023).

Notice that the exercise consists of comparing an economy where lenders are less precise with another where all lenders are Bayesian. Incorporating lenders heterogeneity within the same model would complicate substantially the exercise, still this are interesting inside we may learn from incorporating different type of lenders within the same model.

6.1 Countries

There are two countries $c \in \{l, h\}$ each of them inhabited by a continuum of consumers with the following preferences,

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_{c,t}), \tag{8}$$

where β^t is the discount factor in period t, $c_{c,t}$, is the citizens' consumption from country c in period t, E is the expectation operator, and u is an increasing and strictly concave utility function.

There exists a benevolent government that maximizes citizens' utility. The government can issue a one-period bond, $B_{c,t}$, at the price $q_{c,t}$ and rebates back what it collects or pays from the international bond market.[25] The government budget constraint in period t, conditional on not defaulting, is

$$c_{c,t} \leq y_{c,t} + B_{c,t} - q_{c,t} B_{c,t+1}, \tag{9}$$

where $B_{c,t}$ represents the stock of debt the government carries from the previous period, and $B_{c,t+1}$ is the amount of debt the country issues in the current period, and it matures in period $t+1$, $y_{c,t}$ is the country c's stochastic endowment in period t, and $q_{c,t}$ represents the country bond price.

Every period, the government can declare a default; in this case, it is temporarily excluded from the financial market. In addition, when a country is in default status, it may suffer a direct output loss. Therefore, when the country is out of the market, it faces the following budget

[25] The stock of debt countries can obtain from the market has a lower bound $\underline{B}$, to avoid Ponzi schemes, which is never binding; for technical reasons, I additionally assume the stock of debt to have an upper bound $\bar{B}$.

constraint,

$$c_{c,t} \leq y_{c,t}^{def}, \tag{10}$$

where $y_{c,t}^{def}$ is an exogenous endowment, which is weakly lower than the endowment country c would receive in case of continuing in the market. In the calibration section, I discuss the potential output cost of defaulting and the amount of time countries are excluded from the financial market.

6.2 Lenders

A continuum of identical risk-neutral lenders, i, hold countries' sovereign bonds. They purchase bonds from country c in period t, which will pay 1 dollar in period $t+1$, $b_{c,t+1}^{i}$, in case of country c continues in the market, and zero if country c defaults.

Lenders buy countries' bonds, maximizing their expected profits, $\Pi_{c,t+1}^{i}$, for simplicity I assume that each lender only operates in one country, therefore $\Pi_{c,t+1}^{i}$ is lender i profit operating in country c,

$$E_t(\Pi_{c,t+1}^{i}) = \max_{b_{c,t+1}^{i}} E_t\left[\frac{1-\delta_{c,t}(y_{c,t}, s_{l,t}, B_{c,t+1})}{1+r} b_{c,t+1}^{i} - q_{c,t}(y_{c,t}, s_{l,t}, B_{c,t+1}) b_{c,t+1}^{i}\right], \tag{11}$$

where r is the free risk interest rate, $\delta_{c,t}(y_{c,t}, s_{l,t}, B_{c,t+1})$ is country c default probability which depends on the current country's endowment, $y_{c,t}$, total amount of debt country c issue in period t, $B_{c,t+1}$, and a signal, $s_{l,t}$ which will define later on. Lender price country c bond price, $q_{c,t}(y_{c,t}, s_{\bar{y},t}, B_{c,t+1})$, considering country c default probability, therefore $q_{c,t}(y_{c,t}, s_{\bar{y},t}, B_{c,t+1})$ also depends on the amount of debt, country c endowment and the signal.

The sovereign bond market is perfectly competitive: Lenders compete a la Bertrand, taking as given the countries' total debt when they solve their profit maximization problem. So, in equilibrium, lenders expected profit is equal to zero. Also, in equilibrium, the lenders' total demand of bonds from each country is equal to the total amount of bonds issued by each country, $\int_i b_{c,t+1}^{i} di = B_{c,t+1}$.

Solving the lenders' maximization problem, countries' bond price is equal to one minus the probability of default over the free interest rate,

$$q_{c,t}(y_{c,t}, s_{\bar{y},t}, B_{c,t+1}) = \frac{1 - \delta_{c,t}(y_{c,t}, s_{l,t}, B_{c,t+1})}{1+r}. \tag{12}$$

6.3 Endowment Process

Each period t, countries receive an endowment $y_{c,t}$. Endowments follow an AR(1) process, $y_{c,t} = \rho_c\, y_{c,t-1} + \alpha\bar{y}_t + (1-\alpha)\epsilon_{c,t}$, where $\bar{y}_t$ and ϵ_t follow a normal distribution with zero mean and variance σ^2, and $\rho_c \in (0,1)$. $\bar{y}_t$ represents the common shock to both countries, and $\epsilon_{c,t}$ represents the country c idiosyncratic shock. α is a constant between 0 and 1, which determines the size of the common shocks.

6.4 Information Structure Forecast Updating

Lenders and governments observe a signal, $s_{l,t}$, about country l's future endowment.

$$s_{l,t} = y_{l,t+1} + \epsilon_{s,t}, \tag{13}$$

where $\epsilon_{s,t} \sim N(0, \sigma_s^2)$.

I incorporate the empirical discussion by assuming that lenders believe that the common shocks to both countries are more important than what they are, i.e., they believe in a higher alpha, $\hat{\alpha} > \alpha$. In the calibration, I discuss the specific value of both parameters, $\hat{\alpha}$ and α.

Given the signal lenders, update their forecast about both countries. Regarding country h, lenders use the signal to learn about the common shock.

So, lenders compute the expected value of the common shock conditional on the signal,

$$E(\bar{y} \mid s_{l,t}) = \frac{\frac{1}{\sigma_s^2}}{\frac{1}{\sigma^2} + \frac{1}{\sigma_s^2}} s_{l,t}. \tag{14}$$

Equation 14 is the standard Bayesian updating formula.[26] Then lenders conditional expectation about country h, $E(y_{h,t+1} \mid y_{h,t}, s_{l,t})$,

$$E(y_{h,t+1} \mid y_{h,t}, s_{l,t}) = \rho_h y_{h,t} + \hat{\alpha} E(\bar{y} \mid s_{l,t}), \tag{15}$$

[26] Remember the unconditional expected value of the common shock is zero.

Since $\hat{\alpha} > \alpha$, upon observing the signal they update their beliefs about country h future endowment by more than which belief in the right α would do.

6.5 Timing

The timing within a period is the following: each government starts the period with a stock of debt $B_{c,t}$. Lenders and governments observe countries' endowments and the signal. Governments decide whether to repay their debt or default on its debt. In case of repayment, governments issue new debt $B_{c,t+1}$ taken as given the price schedule $q_{c,t}$. Taken $q_{c,t}$ as given, lenders choose the amount of debt to purchase, b^i. Finally, citizens consume $c_{c,t}$.

6.6 Recursive Equilibrium

Usually, in the endogenous default literature, the set of state variables is the country's stock of debt and endowment; here, we have, in addition, the signal. Then, the sets of state variables are $\mathbf{S}_c = (y_c, s_l, B_c)$.

Governments observe the current endowment and the signal and decide to repay its debt or default, in case of continuing in the market, they issue new debt B_c. $V^o(\mathbf{S}_c)$ represents the country c government decision of defaulting or continue in the debt market, which is the maximum between continue in the market, $V^c(\mathbf{S}_c)$, and defaulting, $V^d(y_c, s_l)$; $V^o(\mathbf{S}_c) = \max\{V^c(\mathbf{S}_c); V^d(y_c, s_l)\}$.

Country c continuation value is,

$$V^c(\mathbf{S}_l) = \max_{B'_c} \; u(y_c + B_c - q_c(y_c, s_l, B'_c)B'_c) + \beta \int_{y'_c} \int_{s'_l} V^o(\mathbf{S}'_c) g_{s_l}(y'_c, y_c) \, f(s'_l) \, dy'_c ds'_l, \tag{16}$$

where the apostrophe, $'$, represents the following period, $g_{s_l}(y'_c, y_c)$ is the government and lenders' density functions of observing y'_c, given the current c endowment conditional on the signal s_l, and $f(s'_l)$ is the distribution of the signal s'_l.

Country c value of being in default,

$$V^d(y_c, s_l) = u(y_c^{def}) + \beta \int_{y_c'} \int_{\bar{s}_y'} \Big[\theta V_c^o(y_c', s_l', 0) + (1-\theta) V^d(y_c', s_l')\Big] \\ g_{s_l}(y_c', y_c)\, f(s_l')\, dy_c' ds_l', \tag{17}$$

where θ is the probability of re-entry into the market after a default. I assume this probability is exogenous to the local economy. Notice that when a country returns to the market after a default, it does so with a stock of debt equal to zero. This is a simplification assumption that is common in the literature.[27]

Country c decides to default on its debt in case the value of being in default is larger than the value of being in the market, $V^d(\mathbf{S}) > V^c(\mathbf{S})$. Let's define the indicator variable $I(\mathbf{S}_c)$, which takes value 1 in case the country c defaults and 0 otherwise,

$$I(\mathbf{S}_c) = \begin{cases} 1 & V^d(y_c, s_l) > V^c(\mathbf{S}_c) \\ 0 & \text{Otherwise.} \end{cases}$$

Lenders lend to the countries as long the return of the bond equals the free interest rate. Therefore, the bond price, q, satisfy:

$$q_{c,t}(y_c, s_l, B_c') = \frac{1 - \int_{s_l'} \int_{y_c'} g_{s_l}(y_c', y_c)\, f(s_l') I(\mathbf{S}'_c)}{1+r}, \tag{18}$$

Definition 1: Markov perfect equilibrium of this economy consists of the policy function $B_c'^*$, the value functions V^o, V^c, V^d, and the bond price function q, such that satisfy equation 16, 17, and 18.

Where $B_c'^*$ is the stock of debt which maximizes the value function V^c

[27](Cruces and Trebesch, 2013) finds a median haircut of 37 percent in their sample of developing and developed countries.

7 Calibration and Simulation

This section presents a preliminary calibration and simulation of the model from Section 6. I calibrate country l (the country receiving the signal) to represent Greece and country h (the country experiencing contagion) to represent Italy. I calibrate the second country to Italy because it is the country that is forecasted the most among the Eurozone periphery countries. However, the same mechanism applies to other countries during the Eurozone periphery crisis. The first subsection discusses the model's parameter choices, and the second subsection presents the model's simulation.

7.1 Calibration

In this subsection, I first discuss the model's functional forms, then the calibration of non-standard parameters in the literature (mainly the size of the common shock), and then the standard parameters in the literature. Each period in the model represents a quarter, so parameters are calibrated on a quarterly basis.

Functional Forms. I use for the simulation a standard utility function,

$$u(c_{c,t}) = \frac{c_{c,t}^{1-\sigma}}{1-\sigma}.$$

where $c_{c,t}$ is the consumption of country c in period t, and σ represents the risk aversion coefficient. As is common in the literature, I calibrate σ to be equal to 2 (Arellano, 2008; Paluszynski, 2023).

The countries' endowment process is calibrated using the logarithmic GDP process:

$$\log(y_{c,t}) = \rho_c \log(y_{c,t-1}) + \alpha\bar{y} + (1-\alpha)\epsilon_{c,t},$$

where $\epsilon_{c,t}$ and $\bar{y}$ follow a normal distribution with mean zero and variance 0.25.

Non-Standard Parameters: Common Shock. The main difference between this model and more standard model (Arellano, 2008; Paluszynski, 2023) is that agents learn from country l to form expectations about country h's next-period endowment.

Thus, the primary parameters for calibration, which are unique to this model, are: (i) the actual size of the common shocks, α, and (ii) the size that lenders (and governments) believe the common shocks to have, $\hat{\alpha}$. I calibrate the actual size of the common shocks to the observed GDP correlation between Greece and Italy. I calibrate agents' beliefs about the common shock size using the cross-country GDP forecast correlation between Greece and Italy from banks.

Table 11 presents the correlation between banks' GDP forecasts for Greece and their forecasts for Italy. The first column shows the correlation for the whole sample, the second column for banks that are less imprecise than the median, the third column for those that are more imprecise than the median, and the last column for the most imprecise 25 percent. Table 11 shows that in all specifications banks show a higher than the actual GDP correlation of 0.156, with greater imprecision associated with higher correlations.

Table 11: Bank Forecast Correlation Between Greek and Italian GDP

	All	Below Median	Above Median	Top 25
	$GDP^f_{b,t,It}$	$GDP^f_{b,t,It}$	$GDP^f_{b,t,It}$	$GDP^f_{b,t,It}$
$GDP^f_{b,t,Gr}$	0.263	0.246	0.286	0.339
	(0.025)	(0.040)	(0.040)	(0.005)
Bank-country FE	Yes	Yes	Yes	Yes
Actual Correlation	0.156	0.156	0.156	0.156
R^2	0.314	0.244	0.429	0.659
Observations	430	196	234	122

Note: This table reports the bank forecast correlation for Italy and Greece. The sample period is between January 2005 and December 2019. Standard errors in parentheses clusterized at the bank country level.

Standard Parameters. A common assumption in the literature is that defaults impose a direct cost on output, which is necessary to countries hold a significant stock of debt. This assumption has empirical support (Hébert and Schreger, 2017). There are different ways to introduce this cost; I follow (Arellano, 2008; Paluszynski, 2023), who assume that when a country is in default, its endowment is the minimum of a fraction of its historical mean and its current realization.

$$y^{def}_{c,t} = \min(\hat{y}, y_{c,t}).$$

where $\hat{y}$ is set to be 3 percent below the historical average, $\hat{y} = 0.97E(y)$, as in (Arellano, 2008; Paluszynski, 2023) among others.

The risk-free interest rate (r) is set at 1.5 percent, corresponding to the median quarterly interest rate on a 10-year German bond. The discount factor is set to 0.97, following (Paluszynski, 2023), who also studies the European sovereign debt crisis. The probability of re-entry is based on (Cruces and Trebesch, 2013), who estimate that developed countries, after a default, take on average 12 quarters to re-enter the market. Table 12 summarizes the main parameters in the calibration.

Table 12: Calibration

Parameter	Description	Value	Source/Target
Non-standard Parameters			
$\alpha^{Bayesian}$	Actual Endowments' Correlation	0.156	Correlation between It-Gr's GDP
$\hat{\alpha}^{Average}$	Lenders' Belief	0.263	It-Gr GDP^f Correlation
$\hat{\alpha}^{Top25}$	Lenders' Belief	0.339	It-Gr GDP^f Correlation
Standard Parameters			
r	Risk free interest rate	1.5	Germany 10 year bond Yield
σ	Risk aversion	2	Literature
β	Discount factor	0.97	Literature
θ	Probability of re-entry	0.083	Cruces and Trebesch (2013)
$\hat{y}$	Output costs	0.97 E(y)	Literature
ρ	Endowment Process Persistance	0.87	Italian GDP persistance
η	Endowment Process variance	0.25	Italian GDP variance

7.2 Simulations

This subsection presents the simulation of the previous model. The main exercise consists of comparing the Italian bond price and default probability when the country faces a less precise lender (and average lender) with the same model where lenders are Bayesian after negative news about the Greek economy.

I simulate the model conditional on a signal equal to a reduction of three standard deviations on Greek endowment, in line with the magnitude of the crisis.[28] A crucial parameter is the signal precision, Which I set equal to the inverse of the variance of the endowment process. Appendix 9 shows how the results change to different signal precision, the main intuition is that as more precise the signal is more relevant is the difference across lenders.

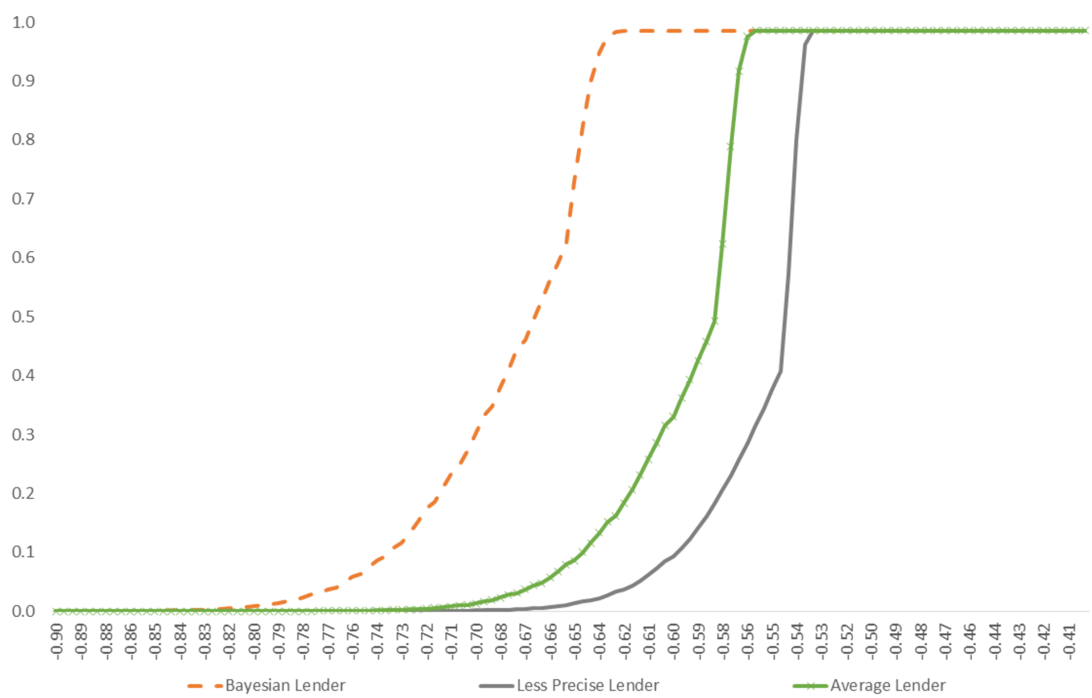
Figure 9 shows the bond price schedules for different lenders when Italy receives an average endowment. The dashed orange line represents the bond price schedule provided by the Bayesian lender, the green line by the average lender, and the grey line by the less precise lenders. The vertical axis indicates the price of a one-dollar bond, while the horizontal axis represents the country's stock of debt. The differences in bond price schedules depend on Italy's stock of debt. For high debt levels, bond prices drop to zero (reflecting a default probability of one), regardless of the

[28]The Greek GDP growth standard deviation before the crisis was 2.8. During the crisis, the GDP around 3 standard deviations.

lender type. In contrast, for low debt levels, bond prices is almost one (reflecting a default probability of zero) for all lenders. The most significant differences across lenders occur when Italy holds an intermediate stock of debt.

For the entire sovereign bond grid (debt levels between 0 and 1), the Bayesian lenders offer a bond price schedule that is 10.91 percent higher than that of less precise lenders and 7.08 percent higher than that of average lenders. For intermediate debt levels (0.4 to 0.9, as shown in the figure), the Bayesian lender provides a bond price schedule which is 21.7 percent higher than the schedule provided by less precise lenders and 14.1 percent higher than the schedule from average lenders.[29] The differences among lenders are most pronounced in this intermediate zone, where the Italian government has a positive, but less than one, probability of defaulting.

Figure 9: Italian Sovereign Bond Price



Note: This figure presents the model simulation's It precise schedule. The vertical axis represents the bond price and the horizontal axis It's stock of debt.

Default Probability. Less precise lenders provide a worse price schedule than the more precise lenders. To analyze the effect of less precise lenders on countries' default probability, I consider

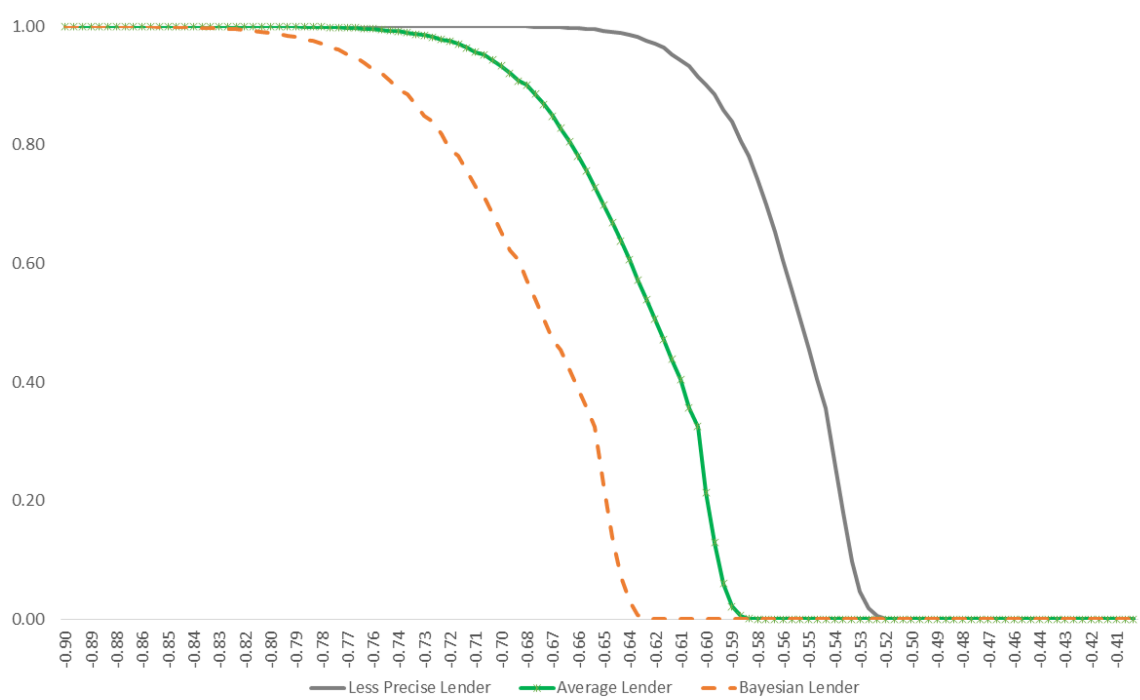
[29]These percentages are calculated as $\frac{1+q^i}{1+q^B}$, where q^i represents the bond price schedule of the average or less precise lender, and q^B is the Bayesian lender's bond price schedule.

two governments with the same belief, one that faces the less precise lenders' price bond schedule and another that faces the Bayesian lenders' bond price schedule.

Figure 10 shows the default probability when the government receives an average endowment under the three scenarios: facing Bayesian lenders (dashed orange line), average lenders (green line), and less precise lenders (grey line). Similar to the bond price functions in Figure 9, the differences between lenders are most pronounced at intermediate stock of debt.

Less precise lenders significantly increase the government's default incentives. For the range of debt shown in the figure (between 0.4 and 0.9), less precise lenders raise Italy's default probability by 21.6 percent compared to the Bayesian lender benchmark, while average lenders increase it by 8.2 percent. Considering the entire range of possible debt levels (between 0 and 1), less precise lenders increase Italy's default probability by 10.86 percent, whereas average lenders raise it by 4.12 percent. Notably, less precise lenders exert a proportionally larger impact on the country's default incentives than average lenders, consistent with their greater effect on Italy's bond price schedule.

Figure 10: Italian Sovereign Bond Price and the Signal Precision



Note: This figure presents the Italian default probability in case it faces Bayesian lenders, orange line, and in case it faces less precise lenders, grey line.

8 Conclusion

This paper shows that, during the Greek crisis, less precise banks adjusted their forecasts and portfolios against other Eurozone periphery countries more significantly, putting additional pressure on these countries' debt rollover processes.

I interpret these findings through a model where banks use categories in making forecasts and portfolio decisions. Banks using coarser categories tend to have less precise forecasts, and when they receive adverse news about one country, they make larger adjustments to forecasts for other countries within the same category.

I incorporate mechanism into a two-country endogenous sovereign default model. Preliminary simulations suggest that less precise lenders reduced Italy's sovereign bond price schedule by 11 more than the Bayesian lenders.

This paper provides a rationalization for the observation that when a country faces a sovereign debt crisis, similar countries often take measures to differentiate themselves from the country where the crisis started. Examples include Argentina's decision to sign the Basel agreements after the Tequila Crisis or the fiscal austerity policies during the Eurozone periphery crisis.[30]

[30](Gibert, 2022) suggests that fiscal austerity policies during the Eurozone periphery crisis helped countries to signal that their situations were more stable than Greece's.

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Appendix

Appendix 1A: Data Statistics Description

Figure 11: Italian Actual Default Probability

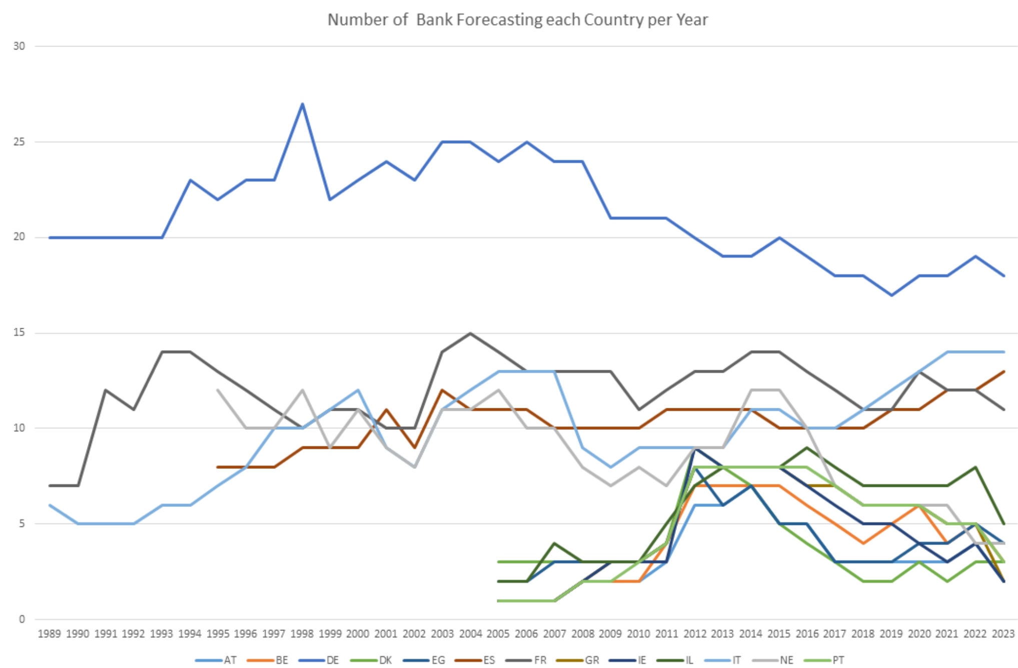
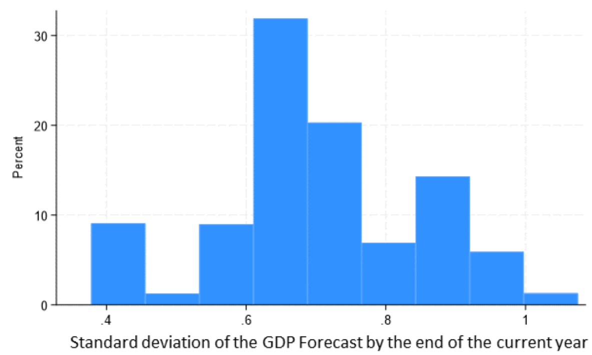


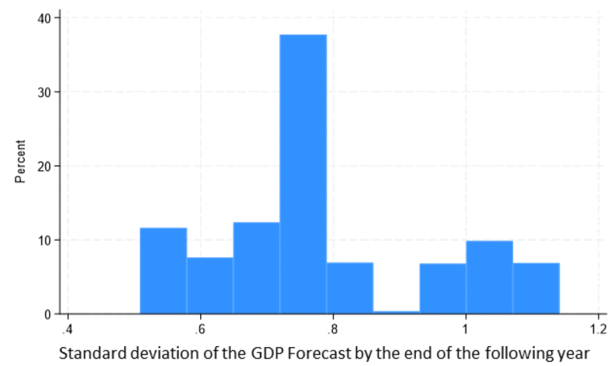
Figure presents two histograms with the bank's GDP forecast standard deviation at the country level for the period between January 2005 and December 2008. On the left, we observe the histogram for the GDP forecast by the end of the current year, and on the right, we observe the forecast by the end of the following year. To have a reference, the median GDP forecast by the end of the current year is 2.2 for this period and 2.1 for the following year. so a standard deviation between 0.5 and 1.2 is relatively large with respect to the median forecast.[31]

Figure presents the histogram of the logarithmic total sovereign bond held by the banks (for banks with a bond portfolio larger than one million euros); Appendix 1 presents other bank balance sheet descriptive statistics.

[31] During the crisis period the bank forecast heterogeneity increased even more, see Appendix 1 for more details.

Figure 12: Bank Forecast Standard Deviation at the Country Level Before the Crisis



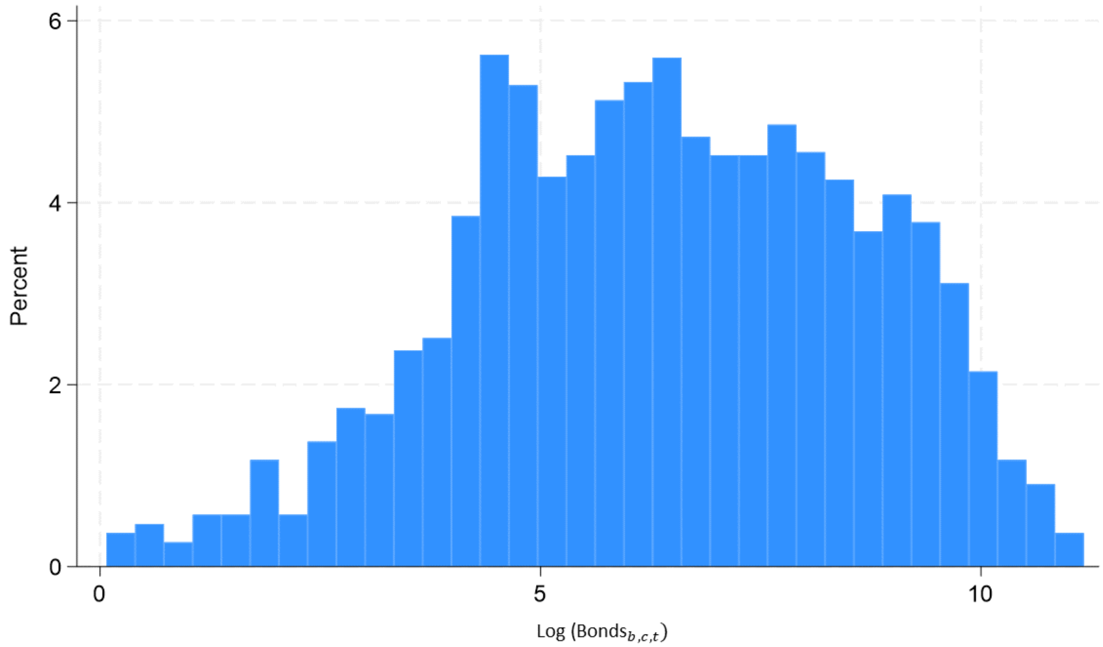


Appendix 1: Bank Imprecision Indicator

I construct four alternative imprecision measure indicator using different periods: (i) using data until December 2007, (ii) using data until May-2008, (iii) between January 2005 and December 2008 and u and (iv) using the whole sample.

Figure 5 shows the correlation between each imprecision measure and the main one. We can observe that in all case the coefficients are positive and significant.

Figure 13: Bank Forecast Standard Deviation at the Country Level Before the Crisis



Appendix 2 A: Robustness check: Robustness check: Different Precision Indicators

This subsection presents the main regression, equation 2 and 3, using alternative imprecision measure. In the first two equation the alternative imprecision measure using the sample period between January 2005 and December 2008, $U_{b,c}^{2005-2008}$, to build up the indicator.

$$x_{b,t+12,t,c}^{f} = \beta U_{b,c}^{2005-2008} \times Crisis_t + \omega_{b,c} + \omega_{t,c},$$

$$x_{b,t+12,t,c}^{f} = \beta U_{b,c}^{2005-2008} \times Yield_{Gr,t-1} + \omega_{b,c} + \omega_{t,c},$$

Table 9 shows that the results are consistent with this alternative imprecision measure: less precise lenders increase their sovereign bond yield forecast and reduce their GDP forecast for the rest of Eurozone periphery during the crisis with respect to the more precise banks.

I perform a similar specification using the alternative imprecision measure constructed with the data until December 2007, $U_{b,c}^{Dec-2007}$, to build up the indicator.

Figure 14: Correlation Between U and alternative U

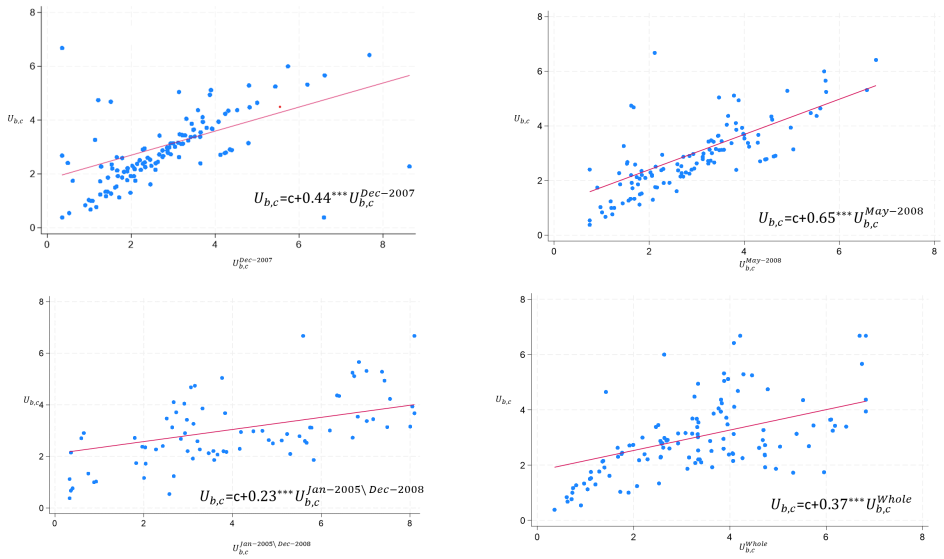


Table 13: Alternative Imprecision Measure

	(1)	(2)	(3)	(4)
	$GDP^f_{b,t+12,t,c}$	$Yield^f_{b,t+12,t,c}$	$GDP^f_{b,t+12,t,c}$	$Yield^f_{b,t+12,t,c}$
$U^{2005-2008}_{b,c} * Crisis_t$	-0.183***	0.062		
	(0.043)	(0.056)		
$U^{2005-2008}_{b,c} * Yield_{Gr,t-1}$			-0.012**	0.014***
			(0.005)	(0.003)
Country#Month FE	Yes	Yes	Yes	Yes
Country#Bank FE	Yes	Yes	Yes	Yes
r2	0.849	0.694	0.847	0.707
N	799	504	799	504

Sample period: January 2008- June 2012. Eurozone Periphery exlcudes Greece.
Standard errors are reported in parentheses and are clustered at the bank-country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$x^f_{b,t+12,t,c} = \beta U^{Dec-2007}_{b,c} \times Crisis_t + \omega_{b,c} + \omega_{t,c},$$

$$x^f_{b,t+12,t,c} = \beta U^{Dec-2007}_{b,c} \times Yield_{Gr,t-1} + \omega_{b,c} + \omega_{t,c},$$

Table 10 shows similar results as table 9. Constructing the imprecision measure with alternative time periods with obtain similar results.

Table 14: Alternative Imprecision Indicator

	(1) $GDP^f_{b,t+12,t,c}$	(2) $Yield^f_{b,t+12,t,c}$	(3) $GDP^f_{b,t+12,t,c}$	(4) $Yield^f_{b,t+12,t,c}$
$U^{<Dec-2007}_{b,c} * Crisis_t$	-0.053	0.108**		
	(0.051)	(0.054)		
$U^{<Dec-2007}_{b,c} * Yield_{Gr,t-1}$			-0.007	0.009*
			(0.005)	(0.005)
Country#Month FE	Yes	Yes	Yes	Yes
Country#Bank FE	Yes	Yes	Yes	Yes
r2	0.841	0.698	0.843	0.698
N	795	504	795	504

Sample period: January 2008- June 2012. Eurozone Periphery exlcudes Greece.
Standard errors are reported in parentheses and are clustered at the bank-country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 2 B: Robustness check: Different Crisis Period

In the previous subsection, I considered the starting point of the financial crisis when Greece asked for the first bailout from the IMF. Nevertheless, there are other potential starting points of the crisis.

To avoid concerns about the previous results being driven by the definition of the starting point of the crisis, I follow two strategies: (i) consider the begging of the crisis in January 2010, when Greece started its ”Stability and Growth Program” (ii) instead of using a dummy variable to define the crisis period using the actual Greek, and the average periphery, sovereign bond yield. The latter is harder to interpret, but it has the advantage that there is no arbitrary decision on the crisis period.[32]

In the first case, I define a dummy variable ($Jan - Crisis_t$) which takes value one between January 2010 and June 2012 and zero; otherwise, then the regression I will estimate is similar to the one in the previous subsection,

$$x^f_{b,t+12,t,c} = \beta Imp_{b,c} \times Jan - Crisis_t + \omega_{b,c} + \omega_{t,c}, \tag{19}$$

Table 12 shows the results for specification 12 in columns 1 and 3 for banks' GDP forecast and

[32]The average periphery sovereign bond consists in the average of Greek, Spain, Italy, and Portugal sovereign bond yield each period.

Table 15: Robustness Check: Different Crisis Starting Date

	Eurozone Periphery		**Eurozone Core**	
	(1)	(2)	(3)	(4)
	$GDP^f_{b,t+12,t,c}$	$Yield^f_{b,t+12,t,c}$	$GDP^f_{b,t+12,t,c}$	$Yield^f_{b,t+12,t,c}$
$U_{b,c} * Crisis - Jan_t$	-0.146*	0.150	-0.098	-0.023
	(0.076)	(0.091)	(0.086)	(0.060)
Country#Time FE	Yes	Yes	Yes	Yes
Country#Bank FE	Yes	Yes	Yes	Yes
r2	0.851	0.724	0.798	0.809
N	724	456	1850	1593
r2	0.850	0.719	0.800	0.809
N	724	456	1850	1593

Sample period: January 2008- June 2012. Eurozone Periphery exlcudes Greece.
Standard errors are reported in parentheses and are clustered at the bank-country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in column 2 and 4 for sovereign bond yield forecast; the first two columns refers to Eurozone Periphery and the last two to Eurozone Core. We observe that during the crisis less precise banks reduced their GDP forecast and increased their sovereign bond yield forecast for Eurozone periphery; however only the former is statistically significant at the 90 percent confident level. On the other hand, we observe no significant differences across bank ex-ante precision forecasting Eurozone core.

	Eurozone Periphery		Eurozone Core	
	(1)	(2)	(3)	(4)
	$GDP^{f}_{b,t+12,t,c}$	$Yield^{f}_{b,t+12,t,c}$	$GDP^{f}_{b,t+12,t,c}$	$Yield^{f}_{b,t+12,t,c}$
$U_{b,c} * Crisis - Oct_t$	-0.178**	0.101	-0.101	-0.033
	(0.064)	(0.084)	(0.083)	(0.064)
Country#Time FE	Yes	Yes	Yes	Yes
Country#Bank FE	Yes	Yes	Yes	Yes
r2	0.851	0.724	0.798	0.809
N	724	456	1850	1593
r2	0.852	0.714	0.800	0.810
N	724	456	1850	1593

Sample period: January 2008- June 2012. Eurozone Periphery exlcudes Greece.

Standard errors are reported in parentheses and are clustered at the bank-country level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 2 C: Dynamic Difference in Difference

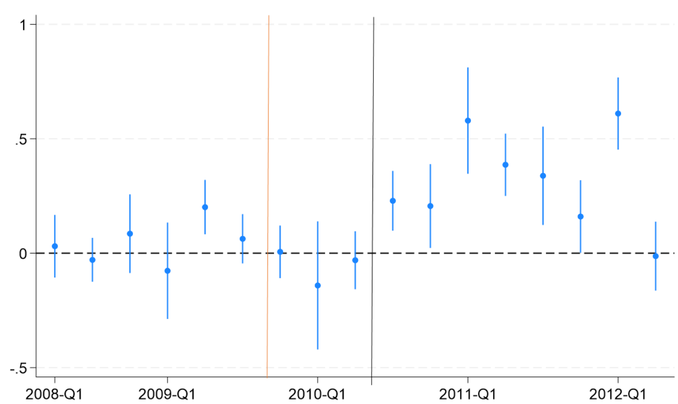
We have seen that less precise banks reduced more their GDP and increased their sovereign bond yield forecasts during the crisis for Eurozone periphery countries than the more precise banks. One potential concern is that differences in trends before the crisis across banks' precision forecasts drive the results. This subsection presents a dynamic difference in difference to mitigate this concern. The estimation I propose is the following,

$$Yield^{f}_{b,t+4,t,c} = \sum_{t} \beta_t Q_t Imp_{b,c} + \omega_{b,c} + \omega_{t,c}, \tag{20}$$

where Q_t is a dummy variable that takes a value equal to one on quarter t and zero; otherwise, Q_t contains all quarters in the sample except Q2-2008; so, we compare the evolution of the banks' forecast differences with this quarter. Notice that in this specification, the regression is quarterly instead of monthly to estimate the parameters with higher precision.[33]

Figure 3 presents the estimation of equation 4 for the period sample between January 2008 and June 2012. We can observe that before the crisis started, the difference across banks' precision forecasting Eurozone periphery sovereign bond yield was around zero, and during the crisis, it started to be positive. The less precise banks forecasted a higher sovereign bond yield for Eurozone periphery countries, excluding Greece, than the more precise banks.

Figure 15: Dynamic Difference in Difference: Sovereign Bond Yield Forecast



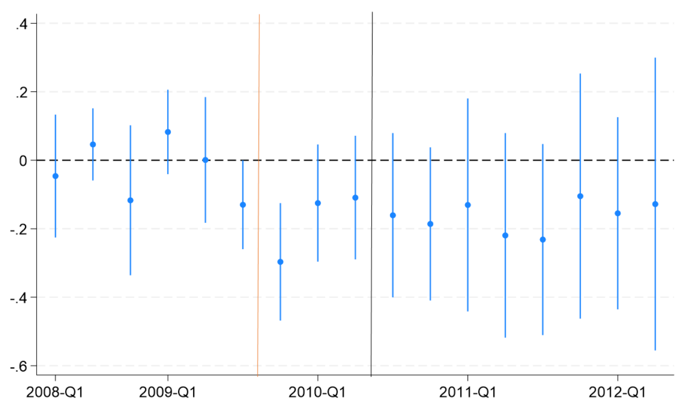
We estimate a similar regression where the dependent variable is the one-year ahead GDP,

[33] regressing a monthly dummy variable instead of quarterly, we obtain similar results, see Appendix 4.

$$GDP^f_{b,t+4,t,c} = \sum_t \beta_t Q_t Imp_{b,c} + \omega_{b,c} + \omega_{t,c}. \tag{21}$$

Figure 4 presents the estimation of equation 5. We observe that before the start of the crisis, there were no significant differences across banks' forecasting precision. During the crisis period, we observe that less precise banks reduced their GDP forecast for the Eurozone periphery; nevertheless, in many quarters, this difference is not significant at the 90 percent level.

Figure 16: Dynamic Difference in Difference: GDP Forecast



Sample period Q1-2008 Q2-2012. Bars represent 90^{th} percent intervals. Standard errors are clustered at the bank-country level.

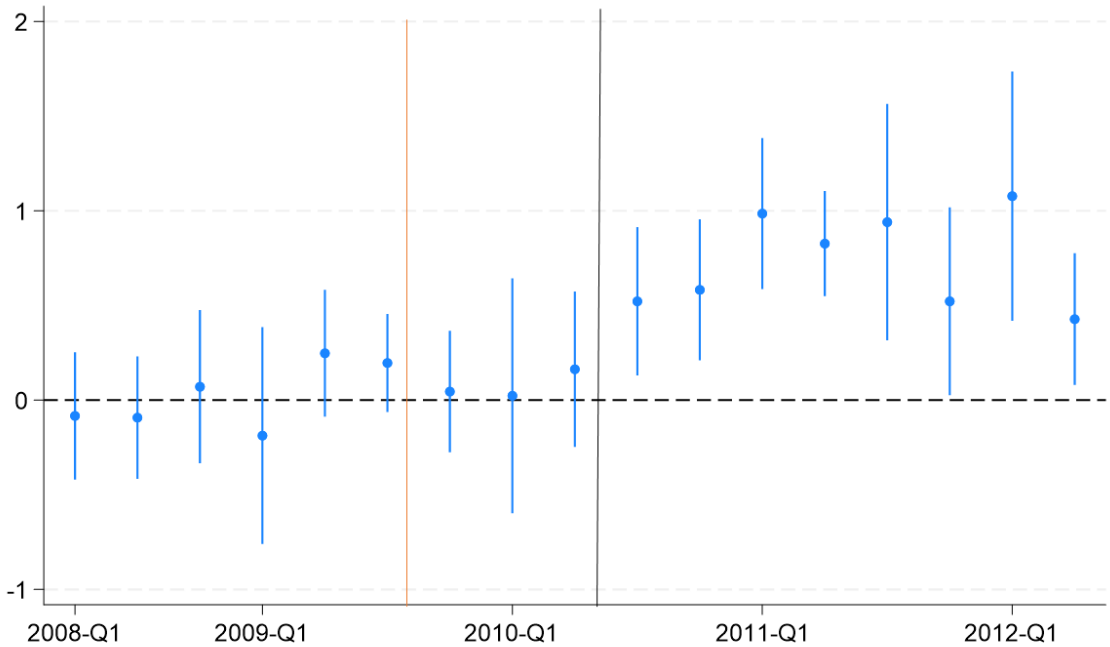
Figure 5 shows a less clear pattern than Figure 4; still, we can observe that after the start of the crisis, less precise banks forecasted a lower GDP for the Eurozone periphery.

Recently, it has been pointed out that continuous treatments, like the imprecision measure, could lead to bias issues in a difference in difference analyses; see, for instance, (Callaway et al., 2021; de Chaisemartin et al., 2022). To mitigate concern in this dimension, Appendix 4 presents the same estimation but uses a discreet measure of bank country imprecision; results are in the same line as we discussed here.

Appendix 2 D: Dynamic Differences in Differences Robustness checks

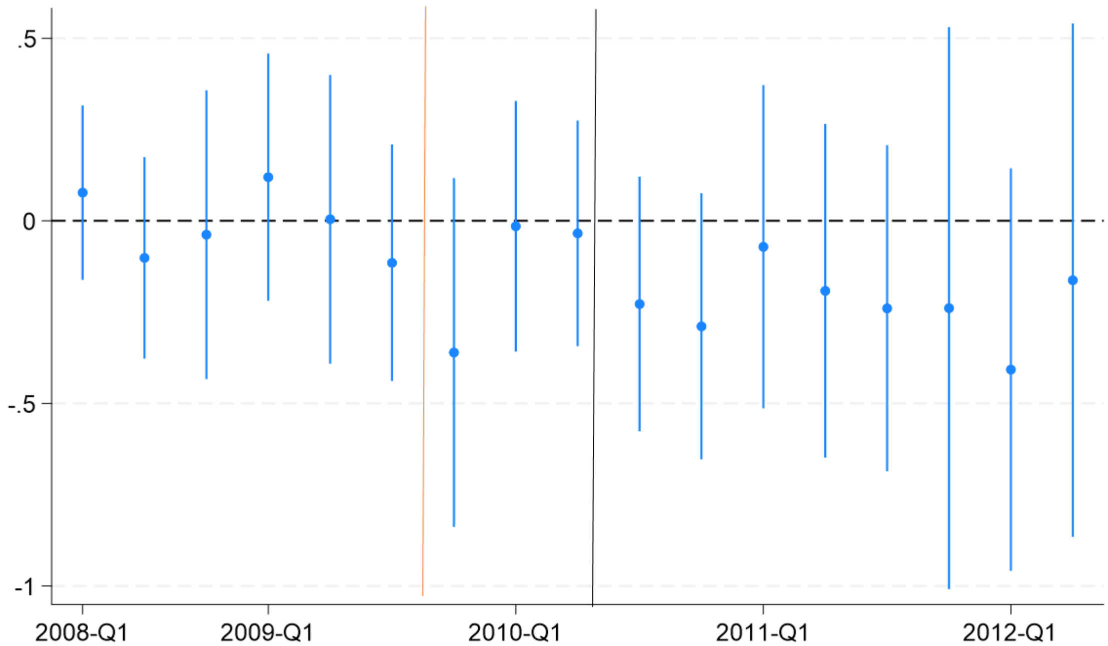
This subsection performs alternative dynamic difference in difference. Figure 8 shows equation 21 and figure 9, equation 22, using a discrete imprecision measure, where banks that are above the 50th percent in the rank of imprecision are considered imprecise and below precise.

Figure 17: Discrete Difference in Difference Discrete Yield



Finally figure 10 presents a monthly regression in line with equation 22, we can observe in this case the regression is more noisy but still we observe the same pattern.

Figure 18: Discrete Difference in Difference Discrete GDP



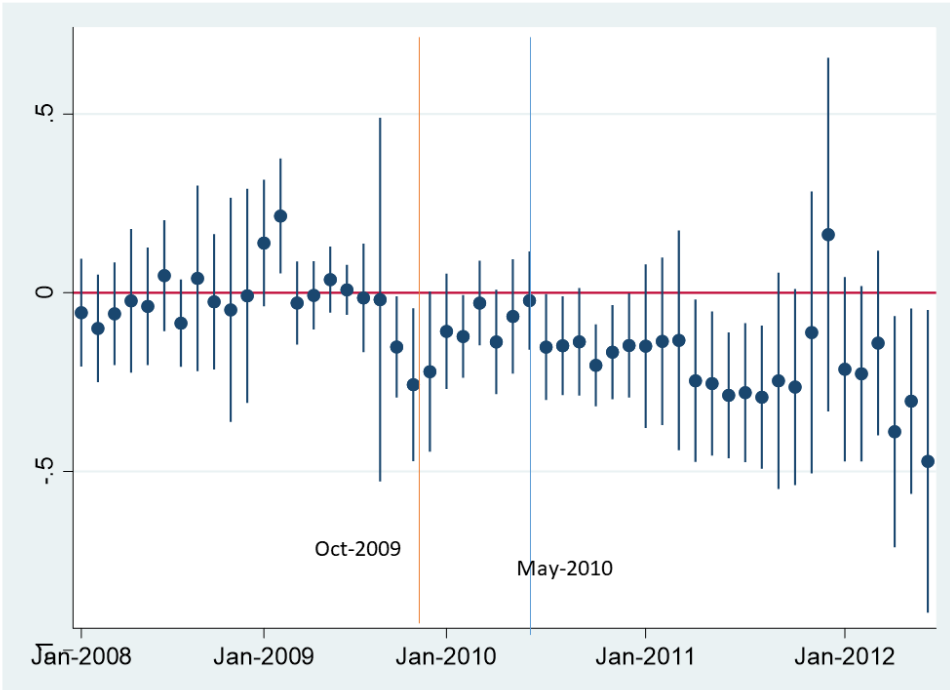
8.1 Appendix 5

Why did less precise banks adjust their portfolio and forecasts relatively more during the crisis? This section proposes the following rationalization: banks classify countries into categories. Some banks use one category for many countries, like the Eurozone periphery, meanwhile others have finer categories, for instance a category per country. Those who use coarser categories tend to have less precise forecasts and upon receiving a news from one country they update their forecasts for the other countries in the same category by more than those with finer categories.

(Swensen, 2009) shows that institutional investors use categorize for organization proposes, like comparing traders' performance. I assume that there is heterogeneity in how lenders classify countries in categories: those lenders who group more countries in one category present coarser categories than those who group fewer countries in each category. I assume the heterogeneity in categorization across banks is exogenous, however in section 2 we discuss that less precise banks are typically smaller, in line with (Swensen, 2009).

To rationalize how categorizes distort lenders forecasts, I follow closely (Bordalo et al., 2012),

Figure 19: Difference in Difference Monthly



and (Bordalo et al., 2016), which have been used to explain professional forecasters' overreaction to macro news, (Bordalo et al., 2020), and to explain extrapolation along financial cycles, (Bordalo et al., 2018). These scholars argue that categorization induce to extrapolation, i.e., upon receiving news about a member of the group, agents adjust their expectations about other members of the group by more than a Bayesian agent would do. Lenders distort the conditional probability of the variable they need to forecast by taking a wrong comparison with an alternative event. Coarser categories induce lenders to take a less relevant event and to distort the conditional expectation more than if they use finer categories.[34]

Formally, consider two countries l and h. Each country receive an exogenous endowment y_c where $c \in \{l, h\}$. y_c follows an AR(1) process, $y_{c,t} = \rho_c \, y_{c,t-1} + \alpha \, \bar{y}_t + (1-\alpha)\epsilon_{c,t}$, with two shocks one which is common to both economies, $\bar{y}$, and another which is idiosyncratic to each country, ϵ_c, both shocks follow a normal distribution with zero mean and variance σ^2, and ρ_c and α are two

[34]There are different micro-foundations to explain why categorization may lead to extrapolation, (Jehiel, 2005, 2022; Bordalo et al., 2023; Spiegler, 2016; Bordalo et al., 2018, 2019, 2012).

constant with values between 0 and 1.[35]

There is a continuous of lenders i, with $i \in [0, 1]$. There are two days and one intermediate period. In day 1, $t = 1$, lenders observe the endowments' realizations, $y_{c,1}$, and they form their priors about the following day endowments, $y^p_{c,2} = \rho_c\, y_{c,1}$. In the intermediate period, lenders observe a signal, s_l, about l second-day endowment, and they forecast h's second-day endowment. On the second day, $t = 2$, lenders observe both countries' endowment realization.

The signal consists of the actual l endowment realization plus an error term, $s_l = y_{l,2} + \epsilon_s$, where ϵ_s follows a normal distribution with mean 0 and variance σ^2_s. Throughout the signal, lenders learn about $\bar{y}$, and update their forecast about h, it is convenient to define $s_l \equiv s_{l,2} - \rho_l y_{l,1} = \alpha\bar{y}_2 + (1-\alpha)\epsilon_{l,2} + \epsilon_s$, which is the new information lenders learn through the signal which is useful to forecast h's endowment.

To fix ideas, let's start considering the case of a Bayesian lender. To update her belief about country h's second-day endowment, she learns about the common shock through the new information about country l,

$$f(\bar{y} \mid s_l) = \frac{f(s_l) f(s_l \mid \bar{y})}{\int f(s_l) f(s_l \mid \bar{y}) dy_{\bar{y}}}, \tag{22}$$

where $f(\bar{y} \mid s_l)$ is the distribution of the common shock, $\bar{y}$, conditional on the signal, s_l, $f(s_l \mid \bar{y})$ is the distribution of the signal conditional on the common shock, and $f(s_l)$ is the distribution of the signal.

Then, the Bayesian lender's forecast is,

$$E(y_{h,2} \mid y_{h,1}, s_l) = \rho_h y_{h,1} + E(\bar{y} \mid s_l), \tag{23}$$

where $E(\bar{y} \mid s_l)$ is the lender Bayesian updating of the common shock expectations.

Let's consider the case of lenders who rely on categories to make their forecasts. Following Bordalo et al. (2012) and Bordalo et al. (2016), some lenders may distort the conditional distribution of the common shock, $\bar{y}$, by taking a wrong comparison. I define $\tilde{s}$ as the alternative event they take as a reference. For instance, they may distort the $\bar{y}$'s conditional probability by comparing with the case that the signal coincides with their priors, such that $\tilde{s} = \rho y_{l,1}$, so $\tilde{s}_{\bar{y}} = \rho y_{l,1} - \rho y_{l,1} = 0$.

[35]This way to write down each endowment process is the same as assuming there shocks are correlated, I am just writing down separately the common component of the process and the idiosyncratic one.

I interpret this case as the signal that does not provide new information about the common shock.

Lenders i distort the density function f by making a wrong comparison with the alternative scenario $\tilde{s}^i$,

$$f^i(\bar{y} \mid s_l) = f(\bar{y} \mid s_l) \left[\frac{f(\bar{y} \mid s_l)}{f(\bar{y} \mid \tilde{s}^i_{\bar{y}})} \right]^{\theta} Z, \tag{24}$$

where $f(\bar{y} \mid \tilde{s}^i_{\bar{y}})$ is the distribution of $\bar{y}$ conditional on $\tilde{s}_{\bar{y}}$, θ indicates the degree of the distortion of lender i, and Z is normalization constant which guaranty the integral of the density function is equal to 1.

The distortion consists in the second term on the right, $\left[\frac{f(\bar{y}|s_l)}{f(\bar{y}|\tilde{s}^i_{\bar{y}})} \right]^{\theta}$, where the conditional density function of interest is divided by the density function of $\bar{y}$ conditional on the alternative event, $\tilde{s}^i_{\bar{y}}$. The closer the alternative event lenders use as a reference to the actual one, the smaller the distortion. In addition, if the case of θ is equal to zero, lender i does not make any distortion, and her expectations coincide with the rational expectation agent, as the larger θ, the larger the degree of the distortion.

I assume that any alternative event lenders use as a reference follow a normal distribution, then since $\bar{y}$ and s_l follow a normal distribution too, the $\bar{y}$'s expectation conditional on s_l is,

$$E^i(\bar{y} \mid s_l) = \theta E(\bar{y} \mid s_l) + \theta \left[E(\bar{y} \mid s_l) - E(\bar{y} \mid \tilde{s^i}_{\bar{y}}) \right]. \tag{25}$$

Therefore, the $\bar{y}$'s conditional expectation is a linear combination between the Bayesian agent expectation and the alternative scenario lenders use. As more relevant the alternative scenario, $\tilde{s^i}_{\bar{y}}$, smaller the distortion.

Then the expectation of lender i abut $y_{2,h}$ is,

$$E^i(y_{h,2} \mid y_{h,1}, s_l) = \rho_h y_{h,1} + E^i(\bar{y} \mid s_l) = \rho_h y_{h,1} + \alpha^i E(\bar{y} \mid s_l). \tag{26}$$

In case of negative news, the lender i expectation is going to be weakly lower than the Bayesian lender; the highest the distortion, the lowest the expected endowment. Since the distorted expectations are a linear combination of the alternative scenario and the Bayesian lender expectation, lenders who distort their expectations present equivalent forecast as if they believe in a higher α than the Bayesian lender.

There is still the question of why some lenders present a bigger distortion than others. I argue that lenders who use finer categories are able to make better comparisons, therefore the alternative event they consider is more relevant (closer to the signal they receive), and distort their expectations less than those who use coarser categories.

Therefore, under this rationalization, we should expect that less precise banks present a stronger correlation between their GDP Greek forecasts and their GDP forecast for rest of the Eurozone periphery than the more precise banks. In the following subsection, I present supportive evidence in favor of this hypothesis.

Appendix 5 discusses other potential explanations. The main alternative hypothesis is that lenders have different priors' precision, the Greek crisis is a signal which all lenders observe with the same precision and so those with less precise priors update their forecast by more. This hypothesis can rationalize Section 3's empirical findings, which are focused on the crisis period, but it is harder to understand why less precise lenders would react differently during a longer period of time, as we show in the following subsection. In addition, Appendix 6 shows that news from Greece presents a stronger negative correlation with less precise bank forecast errors. Which is also hard to rationalize through the alternative hypothesis.

Appendix 5 A: Alternative Potential Rationalization: Rational Investors and Information Frictions

There is one country. Banks need to forecast the country's GDP. There are two forecasters, $i \in \{A, U\}$. There are three periods. In period zero, forecasters form their priors, p_i; in period one, they observe the same signal, S, and make forecasts, f_i, about the country's GDP, and in the last period, they observe the GDP realization.

Forecasters have a prior belief, p_i, which follow a normal distribution with mean $\bar{p}$ and variance equal to α_i^{-1}, $p_i \sim N(\bar{p}, \alpha_i^{-1})$. The signal they observe is such that $S = GDP + \gamma$, where $\gamma \sim N(0, \beta^{-1})$. Agents make their forecasts in period one following a Bayesian updating rule:

$$f_i = E_i(GDP \mid S) = \frac{\alpha_i \bar{p} + \beta S}{\alpha_i^{-1} + \beta^{-1}},$$

where α_i and β are the inverse of prior and signal's variance, respectively.

Since U's signal is more precise relative to his priors than the signal precision A receives relative to her priors, the former will update more her forecast than the latter. This would be the case, for instance, if less precise banks have less precise priors, and the crisis is a signal that all banks observe with the same precision.

One empirical implication of this model is that ex-ante less precise forecasters should reduce their absolute forecast errors regarding the ex-ante more precise forecasters during a crisis.

Appendix 5 B: Alternative Potential Explanation Unawerness

This section presents a model where forecasters are not aware of shocks that generate a negative correlation across Eurozone periphery countries. Therefore, they estimate a higher correlation across Eurozone periphery countries' GDP, and their forecasts are less precise. Therefore, upon receiving a signal about a country in the Eurozone periphery, less precise banks update their forecast about the other countries in the same region more than the more precises.[36]

There are two countries, It and Gr. Each country's GDP depends on two types of random variables: Common variables, $\bar{Y}$, and idiosyncratic variables, ϵ_c, with $c \in \{Gr; It\}$. Within the common variables are two types: $\bar{y}_+$, which generates positive co-movement between countries' GDPs, $\bar{y}_-$ and which generates a negative co-movement between the countries' GDPs.

There are two forecasters, A and U. A is endowed with a model that coincides with the true data-generating process; meanwhile, U possesses a coarser model that does not incorporate the variable ($\bar{y}_-$). Figure 5 represents both forecasters' models in a Directed Acyclic Graph (DAG).

Defining x as the set of random variables: $x = (\bar{y}-, \bar{y}+, \epsilon_{It}, \epsilon_{Gr}, GDP_{Gr}, GDP_{It})$. and p the empirical distribution over x. The DAG is a representation of the following models, forecaster A's model:

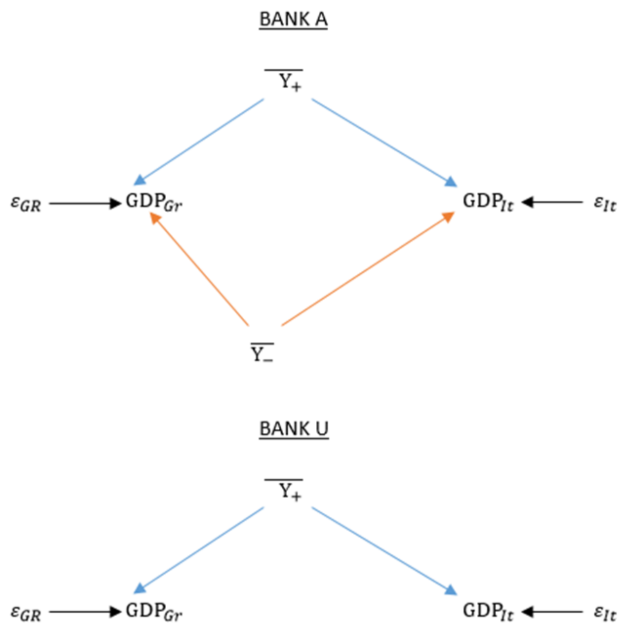
$$p_A(x) = p(\bar{y}_-)p(\bar{y}_+)p(\epsilon_{It})p(\epsilon_{Gr})p(GDP_{Gr} \mid \bar{y}_+, \bar{y}_-, \epsilon_{Gr})p(GDP_{It} \mid \bar{y}_+, \bar{y}_-, \epsilon_{It})$$

and forecaster U's representation,

$$p_U(x) = p(\bar{y}_+)p(\epsilon_{It})p(\epsilon_{Gr})p(GDP_{Gr} \mid \bar{y}_+, \epsilon_{Gr})p(GDP_{It} \mid \bar{y}_+, \epsilon_{It}).$$

[36] There are different ways to rationalize this behavior, see for instance, Jehiel (2005), Jehiel (2022), Bordalo et al. (2023), Spiegler (2016). This section is closely related to Spiegler (2016), who argues that agents might be endowed with misspecified models, which leads to a misestimation of the causal effects (and the correlation) they want to extract from the data. Appendix 4 discusses other potential explanations

Figure 20: Representation of Bank models



.

Forecasters can access to all relevant historical data to estimate their models; therefore, they run regressions to estimate the parameters. To simplify the estimation problem, I assume each random variable is orthogonal to the others, and all the relationships among variables are linear. Therefore, forecasters can run an OLS to estimate the parameters of their models.

Forecaster A will run the following regression:

$$GDP_c = \beta_0 + \beta_1 \epsilon_c + \beta_2 \bar{y}_+ + \beta_3 \bar{y}_-,$$

and forecaster U,

$$GDP_c = \beta_0 + \beta_1 \epsilon_c + \beta_2 \bar{y}_+,$$

There are three periods: in period zero, banks observe the past random variable realizations and estimate their models as we discussed; in period one, forecasters observe a signal, s_{Gr}, about country Gr, and make a forecast about country It; in the last period they observe the countries' GDP. To simplify the exposition, I assume that all variables are iid.

A computes the conditional expectations, $E_t^A(\bar{y}_+ \mid s_{Gr})$ and ${}_t^A(\bar{y}_- \mid s_{Gr})$, and then she uses the expected value of each common random variable to forecast the country It's GDP.

Since U ignores the existence of $\bar{y}_-$, he computes the conditional expectation of $\bar{y}_+$ only: $E_t^U(\bar{y}_+ \mid s_{Gr})$, then, he introduce the expected value of $\bar{y}_+$ into its country It GDP model, and forecasts the country It's GDP. Notice that, after observing a signal about country Gr's GDP, U updates his forecast by a higher amount for the other country than A.

It is worth noticing that A incorporates more information into her GDP forecasts because it considers both common variables ($\bar{y_+}$ and $\bar{y_-}$) in her estimation, so she will present more precise forecasts.

The rationalization provides some empirical predictions: the new information a bank receives about one country in the Eurozone periphery should have predicted power on the forecast errors this bank makes for another country in the same region. Positive news would generate a higher GDP forecast than the actual realization. This correlation is stronger as the bank's model is coarser, i.e., as the bank is more imprecise.[37]

Appendix 5 C: Derivation of Euqation 10

[37] It also predicts a stronger negative correlation when a bank makes a forecast revision for a country within the same region (Eurozone periphery) than when it revises forecasts for the country it is directly forecasting. This observation aligns with the empirical data analyzed in the subsequent section. Appendix 5 discusses this additional prediction.

Appendix 6 A: News from the Eurozone Periphery and Banks reactions

A standard test for rational expectations is to regress the agent's forecast errors on her forecast revision; if the coefficient is different than zero, this would violate rational expectations. Different scholars interpret a negative coefficient as an overreaction and a positive one as an under-reaction; see for instance Bordalo et al. (2020), among others.

We test if less precise banks extrapolate news from Greece to the rest of the Eurozone periphery. To this end I perform equation 7, where I regress the bank GDP forecast error on its forecast revision and the interaction of the forecast revision and the imprecision measure. I also include a bank-country fixed effect which absorb the banks differences in imprecision.

$$GDP\ FE_{b,t,c} = \beta_1 GDP\ RE_{b,t,Gr} + \beta_2 GDP\ RE_{b,t,Gr} \times U_{b,Gr,c} + \omega_{b,c} + \epsilon_{b,t,c}. \tag{27}$$

I perform the regression for the period between January 2005, when all the countries in the Eurozone periphery started to receive forecasts (see Appendix 1), and December 2019, to exclude the pandemic period.

This subsection follows a similar strategy, first I regress bank forecast errors for a country in the Eurozone periphery on the bank forecast revision from another country in the same region. Second, I perform the same regression including the interaction between bank ex-ante precision and the bank forecast revision.

Equation 7 presents the first specification where we regress bank forecast errors for country c on bank forecast revision for another Eurozone periphery country and on a bank-country fixed effects

$$GDP\ FE_{b,t,c} = \beta_1 GDP\ RE_{b,t,l} + \omega_{b,c} + \epsilon_{b,t,c}. \tag{28}$$

Table 7 presents the results of the equation with and without the bank-country fixed effects. The first two rows present the regression when the forecast revision is from Greece, rows 3 and 4 show the results for the forecast revision from Italy, rows 5 and 6 are from Spain, and the last two rows are from Portugal. The forecast errors are for the rest of Eurozone periphery in each case. i.e., for instance in the first row the forecast errors are for Italy, Spain, and Portugal.[38] The sample

[38] We do not have enough data for Ireland to include in this specification.

period is between January 2005, when we start to have more banks forecasting, and December 2019, to exclude the Covid period.

Table 16: Forecast Errors and Forecast Revisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$
$GDP\ RE_{b,t,Gr}$	-0.087*	-0.079*						
	(0.046)	(0.043)						
$GDP\ RE_{b,t,It}$			-0.311**	-0.263**				
			(0.127)	(0.126)				
$GDP\ RE_{b,t,Sp}$					-0.385***	-0.367***		
					(0.144)	(0.127)		
$GDP\ RE_{b,t,Pt}$							-0.576***	-0.521***
							(0.210)	(0.186)
Country#Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
r2	0.004	0.201	0.003	0.163	0.009	0.119	0.022	0.140
N	1425	1424	1745	1743	1339	1339	1345	1344

Standard errors are reported in parentheses and are clustered at the bank-country-year level.
Sample period: March 2005- December 2019.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Notice that, receiving news from a Eurozone periphery country, banks forecast a larger increase in another country's GDP in the same region than the actual realization. In terms of Bordalo et al. (2020), banks overreact to news in the same region. Appendix 5 performs a set of robustness checks as including the Covid period, excluding the period of the crisis, among others. We have similar results in all specifications meaning this seems an average reaction that is not driven by a particular episode.

One important limitation of the analysis is that we only consider those banks that make forecasts for at least two countries in the Eurozone periphery, which is a fraction of the whole sample. It could be that the other banks do not follow the same pattern. However, this subsample is more precise on average than the whole sample; therefore, if something happens, we should expect an attenuation bias.

Equation 8 regresses bank forecast errors of country c on bank forecast revision for another Eurozone periphery country and the interaction between this variable and bank imprecision measure and the imprecision measure itself.

$$GDP\ FE_{b,t,c} = \beta_1 GDP\ RE_{b,t,Gr} + \beta_2 GDP\ RE_{b,t,Gr} \times U_{b,Gr,c} + U_{b,Gr,c} + \epsilon_{b,t,c}. \tag{29}$$

Table 8 presents the results of equation 8 for a forecast revision from each country in the Eurozone periphery. In addition, it shows the results for equation 7 to have a point of reference. In Table 8, the sample is smaller because we only consider the banks that made at least twelve forecasts before December 2008, which is the restriction we impose on the imprecision measure.

Table 17: Forecast Errors and Forecast Revisions

	$GDP\ FE$	$GDP\ FE$	$GDP\ FE$	$GDP\ FE$	$GDP\ FE$	$GDP\ FE$	$GDP\ FE$	$GDP\ FE$
$GDP\ RE_{b,t,Gr}$	-0.075	0.086						
	(0.068)	(0.142)						
$GDP\ FR_{b,Gr} * U_{b,c}$		-0.062						
		(0.049)						
$GDP\ FR_{b,It}$			-0.535**	-0.251				
			(0.205)	(0.351)				
$GDP\ FR_{b,It} * U_{b,c}$				-0.066				
				(0.107)				
$GDP\ FR_{b,Sp}$					-0.529***	0.263		
					(0.161)	(0.254)		
$GDP\ FR_{b,Sp} * U_{b,c}$						-0.225**		
						(0.097)		
$GDP\ FR_{b,Pt}$							-0.234**	-0.123
							(0.092)	(0.153)
$GDP\ FR_{b,Pt} * U_{b,c}$								-0.026
								(0.032)
Country#Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.045	0.047	0.189	0.191	0.171	0.183	0.217	0.218
N	560	560	627	627	623	623	511	511

Standard errors are reported in parentheses and are clustered at the bank-country-year level.
Sample period: March 2005- December 2019.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 8 shows that less precise banks tend to react more to news from the eurozone periphery than the more precise banks. Notice that the negative relation we observed in the previous table seems to be explained by the less precise banks. However, this difference is not always statistically significant, mainly because of small sample issues.

To mitigate the lack of power in the previous regression, I perform equation 7 on a sample with those banks that are more precise than the median bank and the same regression on a sample with the banks that are less precise than the media.[39] Table 9 presents the estimation of equation 7 for the more precise banks in the odd columns and the less precise in the even columns.

We can observe that in all cases, the correlation for the less precise banks is more negative, and

[39] I consider the median bank as imprecise.

Table 18: Forecast Errors and Forecast Revisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$
$GDP\ RE_{b,t,Gr}$	-0.056	-0.113						
	(0.085)	(0.114)						
$GDP\ RE_{b,t,It}$			-0.329	-0.587**				
			(0.317)	(0.243)				
$GDP\ RE_{b,t,Sp}$					-0.101	-0.770***		
					(0.142)	(0.204)		
$GDP\ RE_{b,t,Pt}$							-0.203	-0.292*
							(0.122)	(0.144)
Country#Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.063	0.010	0.016	0.201	0.056	0.200	0.126	0.171
N	365	195	158	469	257	366	331	180

Standard errors are reported in parentheses and are clustered at the Bank-Country-year level.
Sample period: March 2005- December 2019.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in most cases, this correlation is significant.

Finally, we do not observe significant differences across banks' precision when the forecast revision and the forecast error are from the same country,in line with Bordalo et al. (2020). Table 10 shows this regression.

Table 19: Forecast Errors and Forecast Revisions

	(1)	(2)
	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$
$GDP\ RE_{b,t,c}$	-0.392***	-0.378***
	(0.125)	(0.142)
$GDP\ RE_{b,t,c} * U_{b,c}$		-0.002
		(0.027)
Country#Bank FE	Yes	Yes
r2	0.107	0.107
N	2728	2728

Standard errors are reported in parentheses and are clustered at the bank-country-year level.
Sample: Eurozone periphery between March 2005 and December 2019.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results suggest that less precise banks react differently when the news is coming from another Eurozone periphery country.

Appendix 6 B: Robustness check Forecast Errors

Table 14 shows the main regression of section 6, equation 5, including bank-country fixed effects. We obtain results in the same line as table 7. However in this case we lost the significant of the coefficient of interest.

Table 20

	(1) $GDP\ FE_{b,t,c}$	(2) $GDP\ FE_{b,t,c}$
$GDP\ RE_{b,t,Gr}$	-0.224**	-0.080
	(0.083)	(0.138)
$GDP\ RE_{b,t,Gr} * U_{b,c}$		-0.041
		(0.033)
Bank-Country FE	YES	YES
r2	0.127	0.128
N	1274.000	1274.000

Standard errors are reported in parentheses and are clustered at the origin-destination-year.
Sample period: February 2005- August 2023.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15 shows that the results of table 7 are not driven for the crisis period, excluding this period we obtain almost the same coefficient as in the main regression. since we have fewer observation in this case we lost statistically power and the coefficient is not significant.

Table 21

	(1) $GDP\ FE_{b,t,c}$	(2) $GDP\ FE_{b,t,c}$	(3) $GDP\ FE_{b,t,c}$
$GDP\ RE_{b,t,Gr}$	-0.207**	-0.197**	0.001
	(0.095)	(0.093)	(0.137)
$GDP\ RE_{b,t,Gr} * U_{b,c}$			-0.065
			(0.041)
$U_{b,c}$	NO	YES	YES
r2	0.005	0.027	0.028
N	1018.000	1018.000	1018.000

Standard errors are reported in parentheses and are clustered at the origin-destination-year.
Sample period: July 2012- August 2023.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 6 C: Heterogeneity on Bank Reaction Beyond Greek News

If it is true that Banks group together Eurozone Periphery, we should observe that a bank forecast revision from one country in the Eurozone periphery should negatively correlate with this bank forecast errors for another country in the same region.

Therefore, in equation 8 we have the bank b forecast errors for country c as dependent variable as an independent variable the bank b forecast revision for another country l, where l and c represent two different countries in the Eurozone periphery,

$$GDP\ FE_{b,t,c} = \beta_0 + \beta_1 GDP\ RE_{b,t,l} \tag{30}$$

Table 16 presents the results for Equation 8; we can observe that in all cases, a forecast revision from one country in the Eurozone Periphery negatively correlates with this bank forecast errors forecasting another country in the same region.

Table 22

	(1)	(2)	(3)	(4)
	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$
$GDP\ RE_{b,t,Gr}$	-0.191***			
	(0.060)			
$GDP\ RE_{b,t,It}$		-1.854***		
		(0.210)		
$GDP\ RE_{b,t,Es}$			-0.897***	
			(0.211)	
$GDP\ RE_{b,t,Pt}$				-0.980***
				(0.285)
r2	0.009	0.037	0.029	0.026
N	1370	3460	1420	1297

Standard errors are clustered at the bank-country level.
Sample period: between October 1989 and August 2023.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 6 D: Banks reaction to local news

This section perform a similar specification as equation 5, where the news is coming from the same country banks are making the forecast errors. If banks over react to news in general and not just to news from countries in the same region we should observe also a negative β_2 in this case.

$$GDP\ FE_{b,t,c} = \beta_1 GDP\ RE_{b,t,c} + \beta_2 GDP\ RE_{b,t,c} \times Imp_{b,c} + Imp_{b,c} + \epsilon_{b,t,c}. \tag{31}$$

Table 7 shows that there are no significant difference across bank ex-ante precision when the forecast revision is from the same country as the forecast error.

Table 23

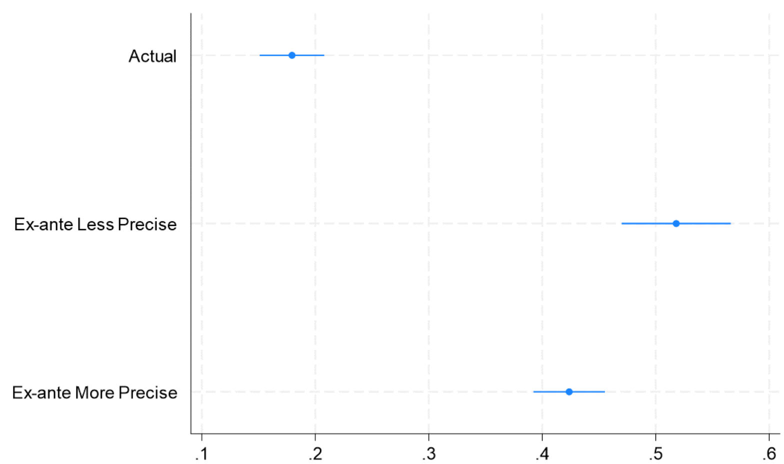
	All	Periphery	Core
	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$	$GDP\ FE_{b,t,c}$
$GDP\ FR_{b,t,c}$	-1.083***	-0.715***	-1.526***
	(0.131)	(0.146)	(0.181)
$GDP\ FR_{b,t,c} * U_{b,c}$	0.008	-0.004	0.013
	(0.008)	(0.008)	(0.030)
$U_{b,c}$	Yes	Yes	Yes
r2	0.098	0.118	0.081
N	11981	4537	7444

Standard errors are reported in parentheses and are clustered at the bank-country level
Sample period between February 2005 and August 2023.

Appendix 7: Correlation Between Greek and Italian GDP Forecast

I break down banks in the fifty percent more imprecise and the fifty percent more precise. Figure 13 shows the average correlation of each group forecast for Greek and Italian GDP. In addition, Figure 13 shows the actual correlations. We can observe that less precise banks present a higher correlation, still more precise banks present a significantly higher correlation than the actual one.

Figure 21: Absolute GDP Forecast Errors



Additionally, I make three principal component analyzes, one for each group and another for the actual variables, where in each case I use the banks Greek and Italian GDP forecast or the actual ones. In the table we can observe that less precise banks presents the largest first component, still it is close in magnitude to the more precise banks.The lowest is the one we obtain with the actual variables.

Table 24

	(1) Actual	(2) Less Precise	(3) More Precise
First Comp Proport GR-IT	0.7198	0.8779	0.8532
First Comp Proport EU-Peri	0.8142	0.9118	0.8951

Appendix 8: Magnitude of the forecast errors during the crisis

The main prediction of the second potential rationalization is that ex-ante less precise banks reduce their absolute forecast errors during a crisis with respect to the ex-ante more precise banks.

To analyze this hypothesis, we can consider the evolution of the forecast errors during the crisis. To this end, this section presents a dynamic difference in difference where the dependent variable is banks absolute GDP and Yield forecast errors, $\mid GDP\, FE_{b,t,c} \mid$, $\mid Yield\, FE_{b,t,c} \mid$, Therefore I perform the following two regressions:

$$\mid Yield\, FE_{b,t,c} \mid = \sum_t \beta_t Q_t \times Imp_{b,c} + \omega_{b,c} + \omega_{t,c} + \epsilon_{b,t,c}, \tag{32}$$

$$\mid GDP\, FE_{b,t,c} \mid = \sum_t \beta_t Q_t \times Imp_{b,c} + \omega_{b,c} + \omega_{t,c} + \epsilon_{b,t,c}, \tag{33}$$

Figures 11 and 12 present the results of equations 29 and 30, respectively. The horizontal red line represents the last quarter of 2009, and the black one the second quarter of 2010 as two potential starting points of the crisis. The blue lines represent a confidence interval of ninety percent.

we observe no shrink banks ex-ante less precise absolute sovereign bond yield forecast error, figure 11, and slightly and no significant decrease in absolute GDP forecast errors, figure 12.

Figure 22: Absolute Sovereign Bond Yield Forecast Errors

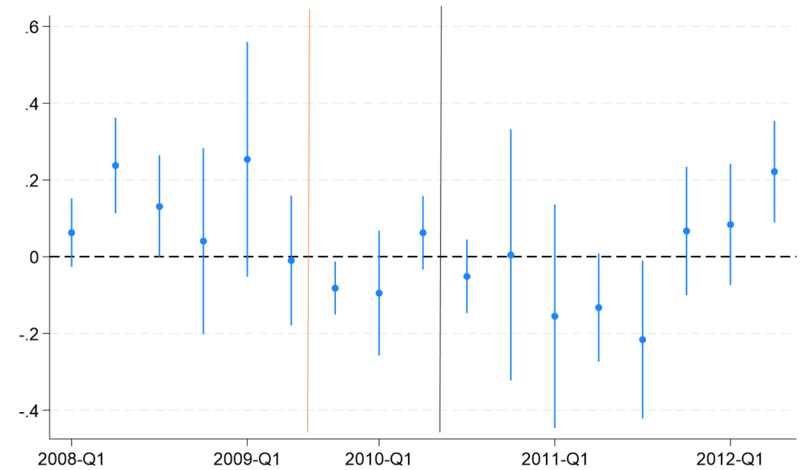
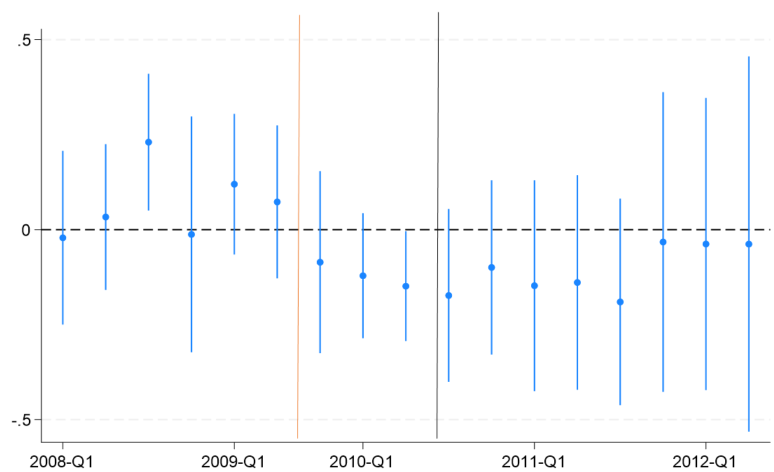


Figure 23: Absolute GDP Forecast Errors

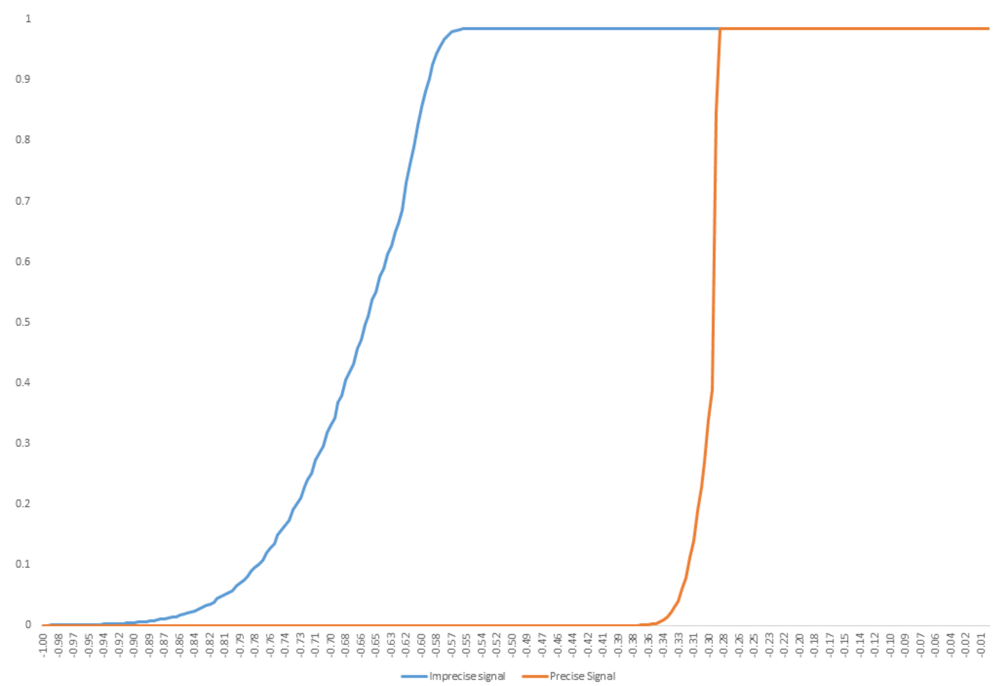


8.2 Appendix 9: Signal Precision

A crucial aspect of the model is the signal precision, in case the signal is very precise, lenders would provide a very low bond price during the crisis; meanwhile, if the signal is very imprecise, we are in a model where lenders do not learn much from the Greek crisis and they update very little they expectations about the Italian endowment, and so they provide a higher bond price to Italy.

To get a sense of the relevance of the signal precision, figure 10 shows the bond price with the average lender in the sample when the signal is two times more precise than the endowment, orange line, and when the precision is half of the endowment, blue line. We can observe that the Italian bond price changes dramatically. In the first case the bond price is very low until the Italian default probability is almost zero, on the other hand, the second case shows a higher price schedule until the Italian stock of debt is really high and so also its default probability.

Figure 24: Italian Sovereign Bond Price and the Signal Precision



This figure presents the model simulation's It precise schedule. The vertical axis represents the bond price and the horizontal axis It's stock of debt.

Lenders' Inflation Expectations, Credit Allocation and Leverage

Filippo De Marco and Diego Friedheim

Preliminary Resutls

September 2, 2024

1 Motivation

When inflation is higher than expected, the value of real liabilities decreases, resulting in a redistribution of resources from lenders to borrowers Doepke and Schneider [2006]. The distributional effects of inflation on lending outcomes however are not straightforward. On the one hand, a positive inflation surprise causes the value of existing loans on banks' balance sheets to drop, leading to a contraction in credit supply. On the other hand, unexpected inflation reduces the debt overhang problem Gomes et al. [2016], increasing investment opportunities and the value of new loans provided to firms. Corhay et al. [2022] utilize a quantitative model to show that the final outcome depends on the health of the financial sector: if the financial sector is financially constrained, inflation could cause a reduction in credit supply that would prevent firms from rebalancing their debt.

This project aims to analyze how lenders' inflation expectations influence their credit allocation. We explore whether banks with higher inflation expectations are more inclined to lend to firms with higher leverage. As described above, firms with significant leverage tend to benefit from an increase in inflation because it reduces the real value of their debt burdens Fisher [1933], thereby increasing their earnings after paying (real) interests and lowering default rates Brunnermeier et al. [2023]. Banks that expect these firms to perform better during inflationary periods should be more willing to extend credit to them in terms of higher credit volumes and lower spreads.

Lenders' expectations are often thought to be an important driver of credit supply and financial crisis cycles (Minsky [1977]; Kindleberger [1978];Greenwood and Hanson [2013]; Fahlenbrach et al. [2018]). For example, Ma et al. [2021] documents that banks' local economic projections matter for bank lending. None of these papers, however, has considered the role of lenders' inflation expectations in the credit allocation across borrowers.

This project is also related to a recent literature showing that beliefs and portfolios are aligned at the individual level for both retail and institutional investors. Giglio et al. [2021], using data from a large survey of sophisticated retail investors from Vanguard, show that beliefs and portfolio choice are positively correlated. Beutel and Weber [2022] provide experimental evidence that individuals' beliefs about expected returns are consistent with their portfolio choices. De Marco et al. [2022] show that banks' foreign yield forecasts, which inversely proxy for sovereign bonds' expected returns, are aligned with their sovereign debt exposures.

2 Methodology

To test this hypothesis our main dataset is Consensus Economics, a survey of professional forecasters polled at a monthly frequency. The survey panelists work for a variety of industry and research institutions, including banks' macro research departments. The survey covers 20 advanced economies (G7 and other countries in West EU) from 2005 until 2023 (some countries like the United States has available data since 1989). We focus on two indicators, namely, yearly inflation and GDP growth forecasts. Crucially, the dataset discloses the name of the individual forecasters, and the forecasts are made by both domestic and foreign institutions. There are 340 unique forecasters, of which 137 are banks. About 41 such banks are large global banks that conduct forecasts for at least 2 distinct countries. The sample is similar to that used in De Marco et al. [2022] and Kalemli-Özcan and Varela [2021].

We match bank forecasts from Consensus Economics with syndicated loan data from the Dealscan database, which is maintained by the Loan Pricing Corporation (LPC Dealscan). LPC Dealscan contains comprehensive information on loans to large firms made by bank syndicates, i.e. a group of lenders, and managed by a lead arranger or lead agent bank. The data encompasses spreads, fees, and other relevant loan characteristics such as maturity, loan size, facility type, collateral, and covenants. Additionally, LPC Dealscan provides information on the country of the borrower and lender and the currency denomination of each loan. Our data collection spans all syndicated loans issued by both private and public companies across all available countries from 2005 to 2023 (and some of them since 1991). While a significant portion of existing studies using LPC data focuses on loans to U.S. corporations, LPC Dealscan also provides information on large non-U.S. loans (Berg et al. [2017]). Using the Dealscan-Compustat Linking Database (Chava and Roberts [2008]) we gather financial statement information from Compustat global database for each borrower.

The matching process produces thirty thousand loans with bank forecast data, firm balance sheet indicators, like the level of leverage, and loans characteristics. Most of the loans are for firms located in US and Canada (arond 60 percent).

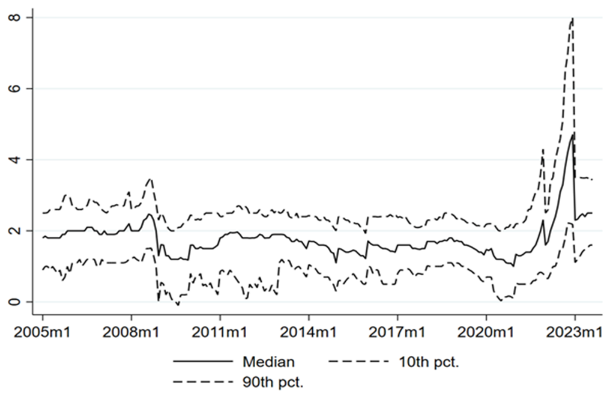
Our baseline specification is:

$$loan_{b,f,c,k,t} = \beta_1 CPI^f_{b,c,t} + \beta_2 CPI^f\ X\ F_{f,t-1} + \gamma GDP^{t+1}_{b,c} + \omega b, t + \omega_f + \omega_{c,k,t} + \epsilon_{b,f,c,k,t} \quad (1)$$

Where $loan_{b,f,c,k,t}$ denotes the log of the loan amount, the average loan life, or the interest rate spread between bank b and firm f located in country c and operating in sector k at time t; $CPI^f_{b,c,t}$ denotes end of the following year inflation forecasts of bank b for country c at time t and $F_{f,t-1}$ represents firm-level leverage. It is important to include bank GDP forecasts as controls, as higher economic growth may affect future inflation, along with bank-time, country-industry-time and firm fixed effects. We expect the estimate of β_2 to be positive and significant when the dependent variable is loan volume or loan duration and negative when the dependent variable is the loan rate, indicating that banks expecting higher inflation extend more credit to firms with higher leverage. To measure firm leverage, we use the ratio of total book debt to total assets.

Identification in the above equation relies on dispersion in bank inflation forecasts for the same target country at the same time. There are two potential concerns with this specification. First, one may question whether there is sufficient variation in bank inflation forecasts during a period of moderate inflation, which covers most of the sample period except for the recent inflation surge in 2021-2022. Figure 1, displayed below, demonstrates that there is indeed substantial dispersion in bank forecasts of inflation around the median. The range between the 90th and 10th of forecasts is approximately equal to the median forecast, hovering around 2 percent for most of the period between 2005 and 2022. This observation is reassuring and indicates that there is ample variation to yield meaningful estimates.

Figure 1: 1-year ahead inflation forecasts



The second concern relates to the potential correlation between bank-specific inflation forecasts and unobservable factors at the bank level. For example, banks expecting higher inflation may also anticipate future monetary policy tightening and larger fiscal deficits. To partially address this, we can control for these factors in the regression, as Consensus Economics also includes forecasts of future short-term rates and budget balance.

3 Preliminary Results

This section presents preliminary results. We observe that banks which expect higher inflation lend higher amount and a lower interest rate to firms with higher leverage, which we compute as the total debt over total assets. We do not observe significant difference in terms of the maturity of the loan.

In the specification we only include the expectations of the lead arrenger of the loan (we exclude the expectations of those banks which are only participant of the deal). In addition we exclude loans which are not active.

Table 1 presents the results for equation 1 when the dependent variable is logarithmic of the amount of the deal. In the first line, We can observe that banks that expect higher inflation make bigger loans to firms with higher debt stock over liabilities, column 4 is the main specification (equation 1), where we include as a control firm characteristics, bank GDP forecast, and fixed effects: firm, country-month and industry-month. Column 5 includes also the bank expectation about the country sovereign bond yield (and its interaction with the firm leverage). The results are robust to this specification, however we do not consider as the main specification because there are fewer banks that report their sovereign bond yield forecast, so we loos around three thousend observations between column 4 and 5.

Table 1: Banks Inflation Forecast and Loans' Amount

	log amount	log amount	log amount	log amount	log amount
CPI_Lleverage_leadnopart	0.145*	0.137*	0.166**	0.167**	0.163*
	(0.078)	(0.077)	(0.074)	(0.080)	(0.086)
CPI_2_leadnopart	-0.017	-0.017	-0.029	-0.010	-0.010
	(0.093)	(0.092)	(0.105)	(0.107)	(0.106)
Lleverage	-0.338	-0.445	-0.389	-0.358	-0.382
	(0.212)	(0.321)	(0.311)	(0.295)	(0.299)
GDP_Lleverage_leadnopart		0.047	0.028	-0.025	-0.059
		(0.075)	(0.075)	(0.073)	(0.078)
GDP_2_leadnopart		0.012	0.019	0.045	-0.057
		(0.140)	(0.139)	(0.147)	(0.166)
Lprofitability			0.049	-0.462	0.514
			(0.479)	(0.526)	(0.522)
CPI_Lprofitability_leadnopart			0.311	0.472**	0.161
			(0.204)	(0.221)	(0.216)
Ltangibility			-0.372	-0.398	-0.274
			(0.293)	(0.273)	(0.262)
CPI_Ltangibility_leadnopart			-0.093	-0.124	-0.154*
			(0.097)	(0.089)	(0.084)
M_Lleverage_leadnopart					0.033
					(0.041)
M_2_leadnopart					0.106
					(0.126)
firm FE	Yes	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes	Yes
Industry(1d)-Month FE	No	No	No	Yes	Yes
r2	0.765	0.766	0.766	0.806	0.818
N	19614	19608	19474	18724	15724

Standard errors in parentheses clusterized at the bank-firm level

For each syndicated deal, We have information at the facility level. The two main facilities are term loans (term) and Revolver lines (credit).[1] There are two main interest rates in this type of loans, the spread over an reference interest rate (the libor for instance), $aisd$, and the fee firms have to pay for drawn new money, $margin$. Table 2 presents the main specification (column 4) for these two type of interest rates in the case of the credit lines.

Table 2: Banks Inflation Forecast and Loans' Margins

	margin_creditline	aisd_creditline
CPI_Lleverage_leadnopart	-16.265	-27.932**
	(10.588)	(10.890)
CPI_2_leadnopart	-24.612**	-9.209
	(11.477)	(12.164)
Lleverage	61.875*	96.298***
	(35.142)	(35.496)
GDP_Lleverage_leadnopart	16.598**	15.109*
	(7.835)	(8.170)
GDP_2_leadnopart	-15.183***	-14.536**
	(5.621)	(6.330)
Lprofitability	-449.051***	-427.418***
	(89.757)	(83.448)
CPI_Lprofitability_leadnopart	97.976***	71.731**
	(32.909)	(32.821)
Ltangibility	-6.190	12.652
	(24.083)	(26.199)
CPI_Ltangibility_leadnopart	16.901**	10.752
	(8.370)	(9.766)
firm FE	Yes	Yes
Country-Month FE	Yes	Yes
Industry(1d)-Month FE	Yes	Yes
r2	0.817	0.816
N	8821.000	8848.000

Standard errors in parentheses clusterized at the bank-firm level

We can observe that banks which expect higher inflation lend cheaper to firms with higher leverage than those which expect a lower inflation. This result together with the previous one are in line with the hypothesis of this project which is that banks that expect higher inflation give better deal conditions to firms with higher leverage than those which expect a lower inflation.

Finally, we present the same specifications as in table one (except for column 5) using as de-

[1] The calcification of Term loans includes Term A, Term B, and term loans, and credit are Revolver lines. In addition, we made other treatments to the data, which are standard in the literature: We winzorized the data at 1 and 99 percentage levels to avoid the results being driven by outliers, we dropped loans which are amendments to existing loans because they could be misreported as new loans, see Roberts (2015) for a discussion of this treatment.

pendent variable the logarithmic of the maturity of the deal (measure in days). We do not observe significant results in this case.

Table 3: Banks Inflation Forecast and Loans' Life

	log (1+days)	log (1+days)	log (1+days)	log (1+days)
CPI_Lleverage_leadnopart	-0.002	-0.003	-0.004	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
CPI_2_leadnopart	0.002	0.002	-0.002	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Lleverage	0.009	-0.005	-0.002	0.004
	(0.005)	(0.006)	(0.007)	(0.008)
GDP_Lleverage_leadnopart		0.006***	0.006***	0.003
		(0.002)	(0.002)	(0.002)
GDP_2_leadnopart		0.004**	0.004**	0.004*
		(0.002)	(0.002)	(0.002)
Lprofitability			-0.013	-0.016
			(0.015)	(0.020)
CPI_Lprofitability_leadnopart			0.014**	0.014
			(0.007)	(0.009)
Ltangibility			-0.012**	-0.013*
			(0.006)	(0.007)
CPI_Ltangibility_leadnopart			0.007***	0.007***
			(0.002)	(0.002)
firm FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes
Industry(1d)-Month FE	No	No	No	Yes
r2	0.959	0.959	0.959	0.964
N	18593.000	18589.000	18463.000	17700.000

Standard errors in parentheses clusterized at the bank-firm level

Long Term Debt. The firm long term debt, topically, presents is not adjusted for inflation, on the other hand the short term debt usually is easier to adjust for inflation. Therefore if the results we are observing are driven by the fisher mechanism we should expect that the effect is driven by the long term debt.

Table 4 presents the results of table 1 dividing firm debt by long term and short term debt. When a firm have high leverage on long term debt banks that expect higher inflation lend more to this firm than banks that expect lower inflation. The first row shows the interaction term between long term debt leverage and bank inflation expectations, we observe that the magnitude of the coefficient is much larger than when we use regular leverage. In addition we observe that the short term debt is not significant.

Table 4: Banks Inflation Forecast and Loans' Life

	log amount	log amount	log amount	log amount	log amount
CPI_long_leadnopart	0.244***	0.226**	0.255***	0.259***	0.228**
	(0.088)	(0.091)	(0.084)	(0.091)	(0.110)
CPI_short_leadnopart	-0.115	-0.078	-0.002	-0.037	0.062
	(0.126)	(0.126)	(0.125)	(0.137)	(0.143)
CPI_2_leadnopart	-0.024	-0.023	-0.051	-0.014	-0.009
	(0.093)	(0.091)	(0.099)	(0.104)	(0.106)
Lst_leverage	0.253	0.589	0.711*	0.496	0.498
	(0.328)	(0.422)	(0.420)	(0.399)	(0.512)
Llt_leverage	-0.569**	-0.779**	-0.730**	-0.638*	-0.711**
	(0.227)	(0.323)	(0.307)	(0.329)	(0.336)
GDP_2_leadnopart		0.015	0.019	0.042	-0.056
		(0.136)	(0.136)	(0.144)	(0.166)
GDP_short_leadnopart		-0.170	-0.236	-0.167	-0.236
		(0.167)	(0.159)	(0.143)	(0.177)
GDP_long_leadnopart		0.093	0.094	0.015	-0.014
		(0.089)	(0.090)	(0.093)	(0.094)
M_Lleverage_leadnopart					0.032
					(0.041)
M_2_leadnopart					0.104
					(0.127)
firm FE	Yes	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	No	Yes	Yes	Yes
Industry(1d)-Month FE	No	No	No	Yes	Yes
r2	0.766	0.766	0.767	0.807	0.818
N	19614.000	19608.000	19452.000	18705.000	15724.000

Standard errors in parentheses clusterized at the bank-firm level

In the same line when we perform a similar regression for the interest rate, we also observe stronger results for long term debt and no significant results for the short term debt. In the first row of table 5, we observe that the magnitude of the coefficient of the long term debt firm leverage times the bank CPI forecast is much stronger than in the previous specification, table 2.

Therefore, the results presented here are in line with the Fisher hypothesis, higher inflation decrease the firm debt burden inducing banks to lend more to higher leverage firm when they expect higher inflation.

Table 5: Banks Inflation Forecast and Loans' Life

	margin_creditline	aisd_creditline
CPI_long_leadnopart	-22.674**	-33.575***
	(11.510)	(12.140)
CPI_short_leadnopart	20.746	5.306
	(25.375)	(30.907)
GDP_short_leadnopart	47.785**	36.381*
	(18.790)	(21.692)
GDP_long_leadnopart	12.429	13.072
	(8.653)	(9.027)
CPI_2_leadnopart	-25.809**	-10.507
	(11.528)	(12.290)
GDP_2_leadnopart	-15.539***	-14.935**
	(5.686)	(6.443)
Lst_leverage	-88.202	-12.408
	(78.335)	(105.673)
Llt_leverage	85.769**	110.253***
	(39.635)	(39.815)
firm FE	Yes	Yes
firm Controls	Yes	Yes
Country-Month FE	Yes	Yes
Industry(1d)-Month FE	Yes	Yes
r2	0.817	0.816
N	8821.000	8848.000

Standard errors in parentheses clusterized at the bank-firm level

4 Conclusion

This paper presents preliminary results in line with the Fisher effect. It shows that banks that expect higher inflation lend more to first with higher leverage than those banks which expect lower inflation.

This effect is driven by the long term debt leverage which is the one which does not adjust by inflation. On the other hand the short term debt which adjust easier by inflation, the interaction of this varialbe with bank inflation forecast does not present significant effect to explain the difference in bank lending.

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Sovereign Default, Expectations and Contagion

Diego Friedheim

November 26, 2024

Abstract

After a sovereign default, lenders may worry about other countries' willingness to pay their debts and demand higher returns. This reaction may pressure countries' rollover debt process, increasing the probability of another default. I incorporate this intuition in a two countries endogenous default model, where countries' fundamentals are correlated. International rational lenders incorporate country's debt decision to update their expectations about the other country's fundamentals and, ultimately, its default probability. I analyze the Tequila Crisis' effect on Argentina through the lens of this model.

1 Introduction

Countries' sovereign defaults often affect other economies. Figure 1 presents the country-bond yields of Latin America's three largest debt holders (Argentina, Brazil, and Mexico) between 1993 and 2000. Disruptive events like Tequila, Asian, Russian, and Brazilian crises have had a sizable impact on the yield of these assets.

Figure 1

Figure 1 shows that a sovereign default, or financial turmoil in general, in one country rapidly affects other countries' sovereign bond yields. Consider, for example, the Tequila Crisis: in December 1994, Mexico defaulted on the part of its debt, starting the crisis; which soon affected Argentinian bonds: in February 1995, the Argentinian sovereign bond yield was almost two times larger than in November 1994, although Argentina had been showing a solid economic performance until the Tequila Crisis.[1]

Argentina and Mexico had presented a synchronous business and political cycle until the Tequila crisis.[2] So, when lenders observed the Mexican crisis, they may have updated their beliefs about Argentinian fundamentals and asked for higher returns to invest in Argentinian bonds.

I introduce this intuition in a two countries endogenous default model. Each country presents a benevolent government that maximizes citizens' welfare by trading a one-period sovereign bond with international lenders. Countries receive an exogenous endowment each period and decide to continue in the market or default on their debts.

There is a continuous of international risk-neutral rational lenders; they price sovereign bonds by computing countries' default probability. Lenders' source of uncertainty is countries' endowments; since endowments are correlated across countries, lenders can obtain information from one country's payment decision to price the other country's bond.

When a country decides to default, lenders update their expectations about the second country's endowment and, ultimately, its default probability. The updating in expectations may pres-

[1] Argentina had presented a growth of over 5 percent each year between 1991 and 1994. In addition, the trade links between both countries were tiny, less than 2 percent.

[2] Both countries show common external shocks and similar political processes. For instance, both countries were at the center of the scene during the Latin American debt crisis in the 80s.

sure the second country's rollover debt process, increasing its default probability. I call this mechanism the expectation channel. The effect of the expectation channel on the second country default probability is regardless of whether the first default occurs for idiosyncratic reasons.

To understand the role of the change in expectations on countries' default probability. I present some preliminary simulations. I calibrate the model to analyze the Tequila crisis effect on the Argentinian economy. The main exercise consists in compare this economy with another where lenders do not learn from another country default decision, which is very close to Arellano [2008]. The simulation shows that the Argentinian bond price decreases significant when Mexico defaults with respect to the alternative model where lenders do not learn from Mexico default decision. However in case Mexico repay the difference in bond price schedule between this economy and one like Arellano [2008] is much smaller.

The outline of this manuscript is as follows: Section 2 revises the related literature, Section 3 presents the model, Section 4 presents a calibration and simulation of the section 3 model, and finally, a conclusion and potential extensions.

2 Related Literature

This manuscript is part of the endogenous default literature, Eaton and Gersovitz [1981], Calvo [1988], Alesina et al. [1989] Cole and Kehoe [2000], Aguiar and Gopinath [2006], Arellano [2008], Lorenzoni and Werning [2019], Cole and Kehoe [2000], Aguiar et al. [2016], Bocola and Dovis [2019], among others. In particular Paluszynski [2023] presents a similar framework where investors learn about a slow motion process. In my model lenders learn about common shocks about both economies which helps to explain the high correlation we observe in sovereign bond prices, specially during crises.

This mechanisms complements the two more common in the literature to explain this phenomena: (i) the renegotiation process, Benjamin and Wright [2009], Arellano et al. [2017], among others, argue that after a sovereign default, the following country in defaulting has more bargaining power and pays lower recoveries. As a result, a default in one country improves the default-negotiation conditions for the next defaulter, increasing its default incentives. (ii) Common risk-averse lenders, Lizarazo [2009], Lizarazo [2013], among others, pose that risk-averse lenders who hold bonds of different countries can account for the co-movement in sovereign bond prices. A default in one country impoverishes lenders, reducing their willingness to buy risky assets, such as emerging bonds. Therefore a sovereign default reduces other emerging bond prices and may induce other defaults.

3 The model

Consider two countries A and M, a continuum of agents inhabiting each country with the following preferences,

$$E_0 \sum_{t=0}^{\infty} \beta^t U(c_{i,t}). \tag{1}$$

Where i indicates the country, t the period, β^t is the discount factor in period t, $c_{i,t}$ is the citizens' consumption from country i in period t, E is the expectation operator, and U is an increasing and strictly concave utility function.

There exists a benevolent government that maximizes citizens' utility. The government can issue a one-period bond (B_i) at the price q_i and rebates back what it collects or pays from the international bond market.[3] The government budget constraint in period t, conditional on not defaulting, is

$$c_{i,t} = y_{i,t} + B_{i,t} - q_{i,t} B_{i,t+1}. \tag{2}$$

Where $B_{i,t}$ represents the stock of debt the government carries from the previous period, and $B_{i,t+1}$ is the amount of debt the country issues in the current period, $q_{i,t}$ represents the country bond price; Finally, $y_{i,t}$ is the country i's stochastic endowment in period t.

Every period, the government can declare a default; in this case, it is temporarily excluded from the financial market. In addition, when a country is in default status, it may suffer a direct output loss. Thereby, when the country is out of the market, it has the following budget constraint,

$$c_{i,t} \leq y_{i,t}^{def}. \tag{3}$$

Where $y_{i,t}^{def}$ is an exogenous endowment, which is weakly lower than the one countries would

[3]The stock of debt countries can obtain from the market has a lower bond $\underline{B}$, to avoid Ponzi schemes, which is never binding; for technical reasons, I additionally assume the stock of debt to have an upper bound$\bar{B}$.

receive in case of continuing in the market. I discuss the potential output cost of defaulting in the quantitative section.

A continuum of identical risk-neutral lenders holds countries' sovereign bonds. They purchase bonds from country i in period t which will pay 1 dollar in period $t+1$ ($B_{i,t+1}$), in case of country i continues in the market, and zero if country i defaults; therefore lenders' expected profits (Π_{t+1}) are,

$$E_t(\Pi_{t+1}) = \int_{y_{i,t+1}} \left[\frac{1-\delta_{i,t}}{1+r} B_{i,t+1} - q_{i,t} B_{i,t+1} \right] dy_{i,t+1}. \tag{4}$$

Where r represents the risk-free interest rate, and $\delta_{i,t}$ represents the lenders' expectation of observing a default of the debt issues in period t.[4] Notice that lenders source of uncertainty is the countries' following period endowments.

Lenders' expected profits are equal to the expected return next period discounted by the risk-free interest rate (the first term on the right-hand side) minus the cost of the bond today (the second term on the right-hand side).[5]

Since they operate in a competitive environment and are risk neutral, the countries' bond prices, in equilibrium, are equal to one minus the default expectation over one plus the risk-free interest rate,

$$q_{i,t} = \frac{1-\delta_{i,t}}{1+r}. \tag{5}$$

3.1 Endowment Process

The endowment process and the information structure (the following subsection) are the two main difference from a more standard model. I assume that the countries' endowment follows an AR(1) process with two shocks, one which is common to both countries ($\bar{y}$) and an idiosyncratic one ϵ_i, so $y_{i,t} = \rho y_{i,t-1} + \alpha \bar{y}_t + (1-\alpha)\epsilon_{i,t}$.

A crucial aspect of the model is the common endowment component. This feature allows lenders to learn from one country's debt decision about the fundamentals of another country. I assume that the common shock impact first to country M and in the following period country A.

[4]Since all investors are identical I neglect investors index

[5]I assume the market value of the debt in default is zero. See Cruces and Trebesch [2013] for an empirical discussion on the actual haircuts.

Therefore, in case of country A, $y_{A,t} = \rho y_{A,t-1} + \alpha \bar{y}_{t-1} + (1-\alpha)\epsilon_{A,t}$ and for country M, $y_{M,t} = \rho y_{M,t-1} + \alpha \bar{y}_t + (1-\alpha)\epsilon_{M,t}$.[6]

3.2 Information Structure

Before the end of the period, each country's government only observes the endowment of its own country and the debt decision of the other country, and the stock of debt the country is carrying from the previous period; at the end of the period, they also observe the other country endowment. I assume each lender only lends to one of the two countries, and she observes the same as the local government.

Thereby, a country M re-pay or default provides information about the country M endowment realization, and country A's government, and lenders for country A update their belief about country M endowment realization. Given their belief about $y_{m,t}$, they also update their belief about country A's next period endowment.

3.3 Timing

The timing of the model is the following: at the beginning of each period countries receive their endowment, country M decides whether to issue new debt and pay the old one or default on it. Then country A also decides between issuing new debt and paying the old one or defaulting. Government A cannot observe country M endowment until the end of the period. At the moment of purchasing new debt of country A, lenders only observe the current endowment of this country and country M's default decision.

3.4 Recursive Equilibrium

This section studies the economy's recursive equilibrium. First, we analyze countries' debts issue and default decisions, and then how lenders price countries' bonds. Country M faces a standard problem, like Arellano [2008]. As it is usual in the literature, we can define the set of country M's state variable $s_M = \{B_M, y_M\}$

[6] This way of introducing the common component across countries allows us to work with a simpler model than assuming the common component affects both countries contemporaneously, and the qualitative results are the same under both assumptions.

$$V_M^c(s_M) = \max_{B'_M} u(y_M + B_M - q_M(B'_M, y_M)B'_M) + \tag{6}$$
$$\beta \int_{y'} V_M^o(s'_M) H(y'_M \mid y_M) dy'_M.$$

Where the apostrophe, $'$, index futures values (one period ahead), V_M^c refers to country M continuation value function, $H(y'_M \mid y_M)$ represents the country M's endowment density function given the previous realization was y_M, V_M^o represents the maximum value between continue in the market, V_M^c, and default, V_M^d, ($V_{M,t}^o = \max\left\{V_{M,t}^c; V_{M,t}^d\right\}$).

Country M's default value function is,

$$V_M^d(y) = u(y_M^{def}) + \beta \int_{y'} \left[\theta V_M^o(0, y') + (1-\theta) V_M^d(y')\right] H(y'_M \mid y_M) dy'_M. \tag{7}$$

Where θ is the probability of re-entry into the market. I assume this probability is exogenous to the local economy. When the country returns to the market after a default, it does with a debt stock equal to zero.[7] The government decides the amount of debt it will issue, according to V^c, and then decides if it will continue in the market or default on its debt.

We can define country M continuation, C_M, and default, D_M, sets,

$$C_M(B_M) = \{y_M \in Y : V_M^c(s_M) \geq V_M^d(y_M)\}, \tag{8}$$

$$D_M(B_M) = \{y_M \in Y : V_M^c(s_M) < V_M^d(y_M)\}. \tag{9}$$

Where Y is the set of possible endowments, the set Y is a subset of the real positive numbers. Therefore, conditional on the stock of debt B_M, when country M's endowment belongs to the continuation (default) set, country M would decide to pay (default) its debt.

There is an indicator variable d_M which represents the country M's debt decision; if country M continues in the market d_M is equal to zero, and if it defaults d_M is equal to one.

[7] This obeys to the assumption that countries' default debt value is zero.

$$d_M(B_M, y_M) = \begin{cases} 0 & V_M^c(s_M) \geq V_M^d(0, y_M) \\ 1 & \text{Otherwise.} \end{cases}$$

Lenders estimate the next period country M's endowment to calculate the country default probability, δ_M,

$$\delta_M(B'_M, y_M) = \int_{D(B'_M)} H(y'_M \mid y_M) dy'_M. \tag{10}$$

The probability of default is defined as the probability of observing a realization of y'_M, which belongs to the default set.

Since lenders operate in a competitive environment, they price country M's debt such that it is equivalent to the probability of repayment over one plus the risk-free interest rate,

$$q_M(B'_M, y_M) = \frac{1 - \delta_M(B'_M, y_M)}{1 + r}. \tag{11}$$

Regarding country A, thanks to the common endowment component, lenders and country A's government can obtain information from country M about the following period country A's endowment. For instance, if country M only defaults in the worse state of nature, then, after country M's default, we are going to observe the lowest $\bar{y}$; on the other hand, if it defaults in all states of the nature, then country M's default is not informative about $\bar{y}$. As a consequence, to form expectations about country A future endowment, in addition to the country M's default decision, they consider country M current stock of debt, B_M, and the previous period endowment, $y_{M,-1}$. I define $s_M^A = \{B_M, y_{M,-1}\}$, and the set $s_A = \{B_A, y_A, s_M^A\}$.

Regarding the value of continuing in the market for country A,

$$\begin{aligned} V_A^c(s_A, d_M) = \max_{B'_A} u(y_A + B_A - q_A(B'_A, y_A, s_M^A, d_M)B'_A) + \\ \beta \int_{y'_A} V_A^o(s'_A, d'_M) G(y'_A \mid y_A, s_M^A, d_M) dy'_A. \end{aligned} \tag{12}$$

Where V_A^c refers to country A continuation value function, V_A^o represents the maximum value between continue in the market, V_A^c, and default ,V_A^d, ($V_{A,t}^o = \max\left\{V_{A,t}^c; V_{a,t}^d\right\}$). $G(y_A' \mid y_A)$ represents the country A's endowment density function given the previous realization was y_A, s_M^A, d_M.

Country A's default value function, $V_{A,t}^d$, is,

$$V_A^d(y_A, s_M^A, d_M) = u(y_A^{def}) + \tag{13}$$
$$\beta \int_{y'} \left[\theta V_A^o(0, y_A', s_M^A{}' d_M') + (1-\theta) V_A^d(y_A')\right] G(y_A' \mid y_A, s_M^A{}', d_M') dy_A'.$$

As country M, when country A declares a default, consumes its default endowment (y_A^{def}), and the following period, with an exogenous probability θ, has the possibility to come back to the market with zero stock of debt.

We can define the set of endowments for which defaulting is optimal for country A, D_A, and the set for which continuing is optimal, C_A,

$$C_A(B_A, s_M^A, d_M) = \{y_A \in Y : V_A^c(s_A) \geq V_A^d(y_A, s_M^A, d_M)\} \tag{14}$$

$$D_A(B_A, s_M^A, d_M) = \{y_A \in Y : V_A^c(s_A) < V_A^d(y_A, s_M^A, d_M)\}. \tag{15}$$

Country A will pay its debt when its endowment belongs to the continuation set. Otherwise, its endowment belongs to the default set, so it will default.

Lenders estimate the next period country A's endowment using also the information they may obtain from country M; to ultimately calculate the default probability,

$$\delta_A(B_A', y_A, s_M^A, d_M) = \int_{D_A} G(y_A' \mid y_A, s_M^A, d_M) dy_A'. \tag{16}$$

The probability of default is defined as the probability of observing a realization of y_M', which belongs to the default set.

Lenders price country A's debt such that its expected payment is equal to the probability of repayment over one plus the risk-free interest rate,

$$q_A(B_A', y_A, s_M^A, d_M) = \frac{1 - \delta_A(B_A', y_A, s_M^A, d_M)}{1+r} \tag{17}$$

Definition 1. The recursive equilibrium of this economy consists of countries' value functions, V_i^c, V_i^d; countries' repayment and default sets, C_i, D_i; countries' citizens' policy function, c_i, government bonds holding, B_i', and countries' bond price function q_i such that

1. Given countries' debt decisions, c_i maximizes countries citizens' utility.
2. Taken as given the bond price function q_A and country A debt policy function B_A', the continuation set C_A and the default set D_A are consistent with government A maximization problem.
3. q_A is consistent with country A default probability and lenders maximization profit problem.
4. Taken as given the bond price q_M and country M debt policy function B_M', the continuation set C_M and the default set D_M are consistent with country M maximization problem.
5. q_M is consistent with country M default probability and lenders maximization profit problem.

3.5 The Expectation Channel

This subsection discusses the effect of a default in country M on country A default probability. The main conclusion of the section is that when country M defaults on its debt, lenders expect a lower endowment for the next period in the country A, weakly lowering its debt price and weakly increasing the default probability.

This subsection borrows a result from the endogenous default literature, which points out that governments have higher incentives to default in recessions. Proposition 1 formalizes this argument for our economy.[8]

Proposition 1. The lower the endowment, the stronger the default incentives: for all $y_1 < y_2$ if $y_1 \in D_i$ then $y_2 \in D_i$.

[8] This result was point out by Arellano [2008]. The previous literature, under complete market assumption, points out that countries default in booms instead of recessions; see for instance Alvarez and Jermann [2000] and Kehoe and Levine [2001]

The result is driven by the incomplete market setting and the strictly concavity of the citizens' utility function. In this environment, it is harder to repay the debt when countries have a lower endowment, which increases government incentives to default.

Given proposition 1, after default in country M, lenders will expect a weakly lower common endowment component. Since A endowment depends linearly on the common component, ultimately a weakly lower country A's endowment than in case country M had paid its debt. Which lead to equation 18 (See Appendix 1 for a derivation of equation 18 from proposition 1.),

$$p(y'_A \geq x \mid y_A, s_M^A, 1) \leq p(y'_A \geq x \mid y_A, s_M^A, 0) \; \forall x \in R_+, \;\; \forall y_A, \;\; \forall S_A. \tag{18}$$

Lenders know that the lower the endowment, the stronger the default incentive (Proposition 1). Therefore after a default in country M, they expect a weakly higher country A default probability.[9] So, when country M defaults its debt country A's bond price is weakly lower than in case country M pays it, which leads to equation 19,

$$q_A(B'_A, y_A, s_M^A, 0) \leq q_A(B'_A, y_A, s_M^A, 0) \;\; \forall B'_A, \; \forall y_A, \; \forall s_M^A. \tag{19}$$

Countries' bond prices reflect the country's default probability therefore the fact that country A bond price is lower when country M defaults with respect to country M does not default implies that country A default set is larger when country M defaults than when country M repays its debt.[10]

$$D_A(B_A, y_A, s_M^A, 1) = \{y_A \in Y : V_A^c(B_A, y_A, s_M^A, 1) < V_A^d(y_A, s_M^A, 1)\}.$$

$$D_A(B_A, y_A, s_M^A, 0) = \{y_A \in Y : V_A^c(B_A, y_A, s_M^A, 0) < V_A^d(y_A, s_M^A, 0)\}.$$

Therefore, we can formalize the expectation channel,

Lemma 1, The expectation channel. A default in country M makes country A default set weakly

[9] The default expectations are strictly higher in case of lenders expect a strictly lower country A endowment, and country A defaults only in some states of nature.

[10] Of course, also two pairs of continuation sets. Here I am focusing on the default sets since I will use it to define the expectation channel.

larger: $D_A(B_A, S_A, 0) \subseteq D_A(B_A, S_A, 1)$.

Continuing in the market depends positively on the price of debt; a lower price reduces countries' incentives to continue in the market, increasing the default incentives. In addition, when the government expects a lower endowment, the continue value reduces more than the default value. This intuition is behind the expectation channel.

4 Model Simulation

This section presents a preliminary model calibration and the numerical solution of the model. The exercise shows a reduction in Argentinian bond price after a Mexico default wit respect to the Arellano [2008] benchmark. In case of Mexico paying its debt we observe a higher price schedule than in the benchmark case.

4.1 Calibration

I calibrate the model for two small open economies as Argentina (A) and Mexico (M); both countries present similar characteristics. A period represents one quarter; therefore, parameters are expressed in quarters at least something different is indicated. I follow closely the Arellano [2008] calibration which will be the benchmark to compare this model.The main difference is how I calculate the endowment process and the estimation of the common shock.

The countries' endowment process is calibrated using the TFP process from the Penn World Table (version 10.0). Each endowment component is drawn from the same AR(1) process. Where the persistence of the process, ρ, is equal to 0.9 and the standard deviation, η, equals 0.025. Which are taken from the Argentinian TFP process.[11] The parameter α is equal to 0.55 matching the correlation between Mexican's TFP lagged one year and Argentinian TFP.[12]

The utility function used for the simulation is the following,

$$u(c_{i,t}) = \frac{c_{i,t}^{1-\sigma}}{1-\sigma}.$$

[11]The period of estimation is between 1973 and 2019. In the case of Mexico, taking the TFP autocorrelation is 0.875 (in this case, the starting point is 1982).

[12]Since TFP frequency is annual, the correlation is between Mexican TFP in $t-1$ and Argentinian in t. The sample period for the estimation stop when the crisis started in 1994.

Where $c_{i,t}$ is the country i consumption in period t, σ represents the risk aversion coefficient and take a value equal to 2, in line with Arellano [2008].

In the model, when countries default, they have an output cost. This is a common assumption in the literature, which allows models to support a larger range of debt. In addition, it has empirical support, see for instance Hébert and Schreger [2017] and Borensztein and Panizza [2009]. Therefore, when a country is in default status, its endowment is the minimum between a fraction of the historical mean and the current realization.

$$y_{i,t}^{def} = \min(\hat{y}, y_{i,t}).$$

Where $\hat{y}$ is an endowment 3 percent lower than the historical average ($\hat{y} = 0.97E(y)$); which is standard in the literature, see for instance Arellano [2008], Paluszynski [2023].

The risk-free interest rate (r) is equal to 1.7 percent, which is the median quarterly interest rate of a US-5 years bond during the period of the Tequila crisis. Following Arellano's calibration, I parametrize the discount factor equal to 0.953 to reach a 3 percent default probability. Finally, the re-entry probability equals 0.282 in line with the literature.

4.2 Simulations

I focus here in country A which is the most interesting case, the main exercise consists in comparing country A economy when country M defaults and when it pays its debt with a benchmark economy where lenders do not learn from Mexican default decision.

At the moment of the crisis, the Mexican (non-financial) public sector held a stock of debt over GDP of 27.1 percent, and the country's GDP was growing by 6.6 percentage points. In this scenario, after Mexico defaults (pays) its debt, lenders will expect a five percent lower (0.0075 higher) endowment in Argentina. The magnitude of the expectation channel depends also on Argentinian economic conditions: at the moment of the crisis, Argentina presented a GDP growth of 5 percent in 1994.[13]

Figure 2 shows country A bond price on axis y for different levels of debt, axis x, when country M defaults its debt, grey line, when it pays, orange line, and the blue line is the benchmark economy where lenders do not learn from Mexican debt decision, very similar to Arellano econ-

[13]The source of this data is CEPAL.

omy (with a different endowment process calibration).[14] We can observe that a default in Mexico decreases Argentinian bond price, because lenders expect a lower endowment and so a higher default probability. On the other side, when Mexico repays its debt, this decision also provides information about the common shock; therefore, the Argentinian bond price schedule is higher than the one in the benchmark economy.

Figure 2

In this exercise, I am assuming that lenders obtain information from Mexico with the same precision as with the Argentinian economy. It could be the case that lenders do not observe the Mexican economy with the same precision as they observe the Argentinian economy. In this case, the effect would be smaller. Figure 3 shows the same exercise where lenders obtain information about the Mexican economy with half of the precision than they obtain about the Argentinian economy, in this case we observe the same pattern as in figure 2 but the difference with the benchmark economy are attenuated.

Figure 3

5 Conclusion and Potential Extensions

This manuscript endogenizes a mechanism through which a default in one country may affect lenders' expectations about other country repayment ability and, in the end, its default probability. This mechanism complements and potentially reinforces other mechanisms existing in the literature as risk-averse lenders and changes in the renegotiation conditions.

Finally, this manuscript opens other research questions regarding potential policy implications. For example, could a government send a signal about its current fundamentals? Would this prevent contagion? During financial turmoils, it is common to observe governments' efforts

[14] I assume Argentina received an endowment 3 percent higher than its average in the previous period. According to the Argentinian GDP growth in 1994. It is worth noticing that, in case country M defaults, country A cannot obtain information from the country M's next-period debt decision. To have the same dimensional in both exercises, I assume in the case of paying the debt, the government and lenders cannot obtain new information from the next period country M debt payment.

to provide information about their current economic situation through announcements, and bilateral agreements, among others, as Argentina did during the Tequila crisis. The expectation channel could be one explanation for this behavior.

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6 Figures

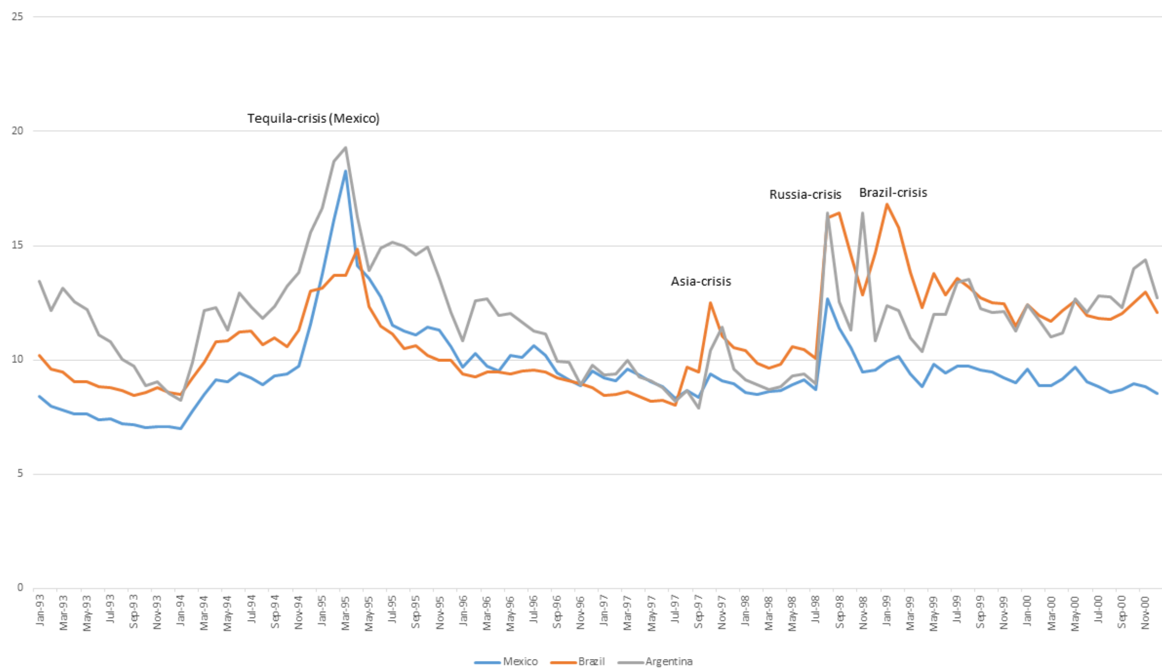

Figure 1: Emerging Bonds Yield during Episodes of Financial Crisis

Vertical axis shows the sovereign bonds yield in percentages points. Source: own elaboration based on Bloomberg

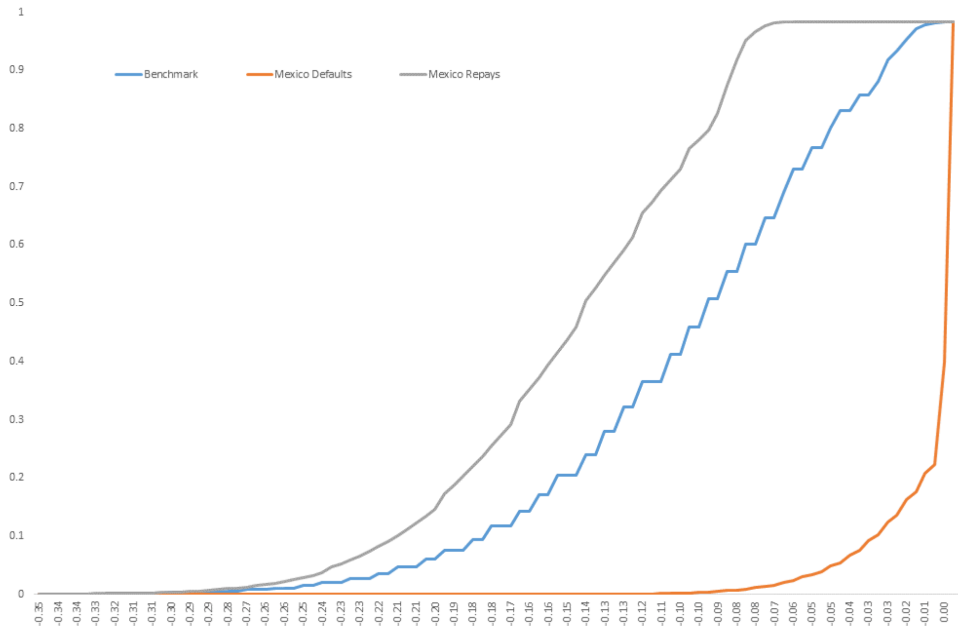

Figure 2: Bond price

This figure presents the Argentinian bond price for different levels of debt: in case Mexico defaults (grey line), in case it pays its debt (orange line), and for the benchmark (blue line).

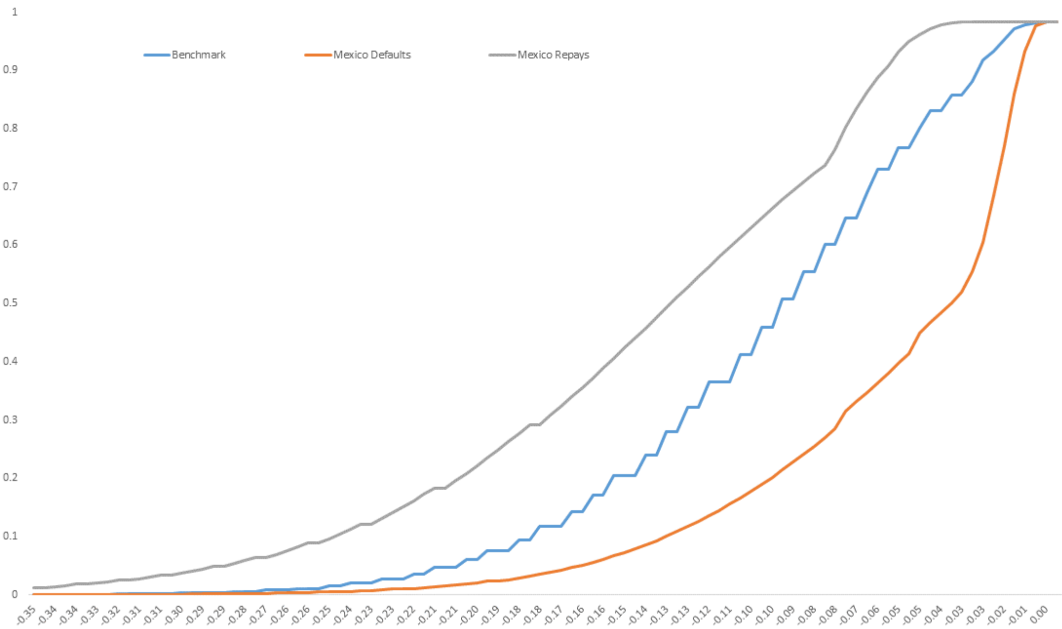

Figure 3: Bond price (Less Precision)

This figure presents the Argentinian bond price for different levels of debt; in case of Mexico defaults (grey line), in case pays its debt (orange line), and for the benchmark (blue line)

7 Appendix 1

This section presents a proof of equation 18. Let's start from Arellano [2008] result, that countries default when they receive a low endowment. Therefore, the expected value of the common component conditional on country M repaying stochastic dominates if country M defaults,

$$p(y_M \geq x \mid s_M^A, 1) \leq p(y_M \geq x \mid s_M^A, 0) \; \forall x \in R_+, \;\; \forall \; \forall s_M^A.$$

Since y_M depends linearly on $\bar{y}$, $y_M = \alpha \bar{y} + (1-\alpha)\epsilon_M$, then

$$p(\bar{y} \geq x \mid s_M^A, 1) \leq p(\bar{y} \geq x \mid s_M^A, 0) \; \forall x \in R_+, \;\; \forall \; \forall s_M^A.$$

Also, y'_A depends linearly on $\bar{y}$, $y'_A = \alpha \bar{y} + (1-\alpha){\epsilon'}_{A'}$, then,

$$p(y'_A \geq x \mid s_M^A, 1) \leq p(y'_A \geq x \mid s_M^A, 0) \; \forall x \in R_+, \;\; \forall \; \forall s_M^A.$$

Finally, given the y_A is an AR(1) process, conditioning on the current country A's endowment realization do not reverse the result.

$$p(y'_A \geq x \mid y_A, s_M^A, 1) \leq p(y'_A \geq x \mid y_A, s_M^A, 0) \; \forall x \in R_+, \;\; \forall \; \forall s_M^A.$$