The Asymmetric Pass-Through of Sovereign Risk

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Abstract

This paper studies the macroeconomic effects of increases in corporate risk around sovereign debt crises. I use a heteroskedasticity-based approach to estimate the causal effect of sovereign risk on the credit risk of non-financial firms. Using Italian firm-level data for the last European debt crisis, I find that sovereign risk accounts for almost a third of the total increase in corporate risk and that this effect is stronger for riskier firms. I use bank-level data to show that the bank-lending channel plays an important role in this transmission. I find that banks with higher sovereign debt holdings exhibit a larger increase in their corporate non-performing loans. Increases in sovereign risk thus weaken banks' balance sheets directly, by decreasing the value of government bonds held by banks, and indirectly, through banks' exposures to non-financial firms. I formulate a heterogeneous-firms model where the banking sector transmits sovereign risk to firms and show it is able to match the empirical relationships estimated from Italian data. In a counterfactual analysis, I find that corporate risk represents a quantitatively important feedback mechanism that further deteriorates banks' balance sheets, amplifying the size and persistence of a sovereign debt crisis. I study different policies that can mitigate the negative effects of sovereign risk and identify efficiency gains from policies that exploit firms' heterogeneous reactions to increases in sovereign risk.

Keywords: Sovereign risk, corporate risk, financial contagion, heterogeneous-agent models.
JEL codes: E44, F34, G15, G18.

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1 Introduction

Why are sovereign debt crises characterized by large and persistent declines in economic activity? One common explanation in the literature is based on the exposure of domestic financial intermediaries to sovereign debt. Because domestic banks hold a large share of government bonds, increases in sovereign risk weaken banks' balance sheets, tightening the supply of credit to non-financial firms and propagating the sovereign shock to the real economy (Bottero et al., 2020, Arellano et al., 2019, Buera and Karmakar, 2018, Bocola, 2016, Gennaioli et al., 2014). In this paper, I show that this compelling narrative for the effects of sovereign risk on private investment and output is missing a key ingredient: corporate risk. I show that a rise in sovereign risk causes a significant increase in non-financial default risk and that banks play an important role in this transmission. An increase in corporate risk not only affects firms' investment and demand for credit, but also decreases banks' net worth, due to banks' exposures to non-financial firms. This effect is quantitatively important given the size of the exposure. For European banks, for instance, loans to the non-financial sector are four times larger than their sovereign holdings. To quantify how much of the decline in real activity is explained by this sovereign-to-corporate-risk channel, I formulate a quantitative model in which non-financial risk is endogenously linked to sovereign risk through the banking sector.

In the first part of the paper, I provide empirical evidence of the importance of the sovereign-to-corporate-risk channel. I show that increases in sovereign risk lead to significant increases in corporate risk, and describe important asymmetric effects across firms behind this transmission. In particular, the increase in sovereign risk leads to an almost one-to-one increase in corporate risk in the case of the riskiest firms, but safer firms remain mostly unaffected. I then present evidence that highlights the role of the bank-lending channel in this transmission. I show that banks with larger sovereign debt holdings (i.e., the banks that are more affected by an increase in sovereign risk) exhibit a larger increase in their corporate non-performing loans that further weakens their balance sheets. Taken together, these results imply that an increase in sovereign risk affects banks' balance sheets not only directly, by decreasing the value of government bonds held by banks, but also indirectly through banks' exposures to non-financial firms.

The main identification challenge when estimating the transmission of sovereign to corporate risk is that sovereign risk may increase in response to deteriorating economic conditions that lead to an increase in corporate risk. To identify the causal link, I use Italian data to study changes in the default risk of publicly traded non-financial firms around "foreign news events." These events include news about credit-rating downgrades and bailouts for two other European countries, Greece and Portugal, during April 2010 - April 2012. The identifying assumption is that these events do not directly affect Italian fundamentals but are likely to affect Italian sovereign risk through contagion.[1] There are

[1]Contagion is defined as a largely unpredictable, higher correlation across countries during crisis times than during normal times (Pesaran and Pick, 2004). Ludwig (2014), Beirne and Fratzscher (2013), Giordano et al. (2013), Mink and de Haan (2013), and Kalbaska and Gatkowski (2012) have all shown the presence of cross-country sovereign contagion during the last European debt crisis.

four underlying assumptions behind this identification strategy. First, the news events are not driven by Italian fundamentals. For instance, the decision by a risk agency company to downgrade the sovereign credit rating of Greece or Portugal does not depend on the economic conditions of Italy. Second, Italian firms are not directly affected by these events. Third, there are no omitted common factors around these events (e.g., a change in the market price of risk) that lead to an increase in sovereign risk and, at the same time, cause an increase in corporate risk. Fourth, the market does not fully anticipate these events. In Section 2, I argue why these are reasonable assumptions, provide evidence, and discuss potential challenges to the identification.

I employ a heteroskedasticity-based approach (Rigobon and Sack, 2004) to identify the causal effect. The methodology relies on the identifying assumption that the variance of the shocks to Italian sovereign risk is higher around the news events, whereas the variance of the shocks to corporate risk (and other potential common factors) remains the same. I use 10-year Italian credit default swaps (CDS) as a measure of sovereign risk, and I construct a high-frequency measure of non-financial credit risk based on the Merton (1974) distance-to-default framework. I show that sovereign risk leads to a significant increase in the default probability of non-financial firms. Every 1pp increase in Italian CDS causes a 0.29pp increase in corporate risk. After linearly extrapolating these results to the entire period, the estimates can explain a third of the total increase in non-financial default risk. In addition, I show that there are important asymmetries across firms behind this transmission. Non-financial firms with higher pre-crisis default risk are significantly more affected and their default risk moves almost one to one with respect to Italian CDS. Corporate risk for safer firms, on the other hand, does not react significantly to changes in sovereign risk.

Although sovereign risk could affect corporate risk through several channels, I focus on the role of the bank-lending channel and provide evidence of its significance.[2] To quantify this channel, I use Italian bank-level data to exploit the regional heterogeneity across banks' sovereign exposures. The underlying idea is that banks with larger sovereign exposures are more affected by increases in sovereign risk, and they pass on part of this risk to their corporate clients. When firms operating with these banks try to roll over their debt, they may be required to meet higher credit standards (e.g., larger collateral), they may face a higher spread, or they simply will not be able to roll over their debt. The higher difficulties in rolling over their debt may induce more firms to default on their current loans, increasing corporate risk. Consistent with this idea, I show that a larger (pre-crisis) sovereign exposure is associated with a larger increase in corporate non-performing loans (NPLs), even after controlling for many bank characteristics that capture the credit quality of banks' loan portfolios. For two banks that are one standard deviation apart in terms of their pre-crisis sovereign exposures, the bank with a higher exposure exhibits

[2] Borensztein and Panizza (2009) discuss and provide empirical evidence for different channels through which sovereign risk can affect the non-financial firms. Mendoza and Yue (2012) provide a microfoundation based on an imperfect substitution of imported inputs for domestic inputs. Kaas et al. (2020) and Roldan (2020) provide microfoundations based on taxes and aggregate wealth effects.

an additional 15pp increase in the growth rate of NPLs, which represents almost 20% of the total increase in Italian NPLs during the crisis. The analysis, therefore, implies that the bank-lending channel plays an important role in the transmission of sovereign to corporate risk.

To quantify and gain a deeper understanding of the real implications of the sovereign-to-corporate-risk channel, I formulate a heterogeneous-firms model that captures the feedback between corporate risk and banks' net worth. The model is composed of three sectors: heterogeneous non-financial firms, a government, and households/bankers. The key ingredient of the model is that firms' default risk is endogenously linked to sovereign risk through the banking sector, and I use the empirical estimates to discipline this relation.

The model assumes a continuum of risk-neutral firms that are heterogeneous in their size, leverage, and productivity. Firms hire labor and use their own stock of capital to produce the (unique) final good of the economy. Purchases of capital can be financed with internal resources or by issuing debt in the form of long-term loans. Firms lack commitment and can default on their stock of loans. The supply of credit is provided by the domestic bankers, which are owned by the households. To finance their loans, each banker uses its own net worth and households' deposits. Similarly to Gertler and Karadi (2011), I introduce an agency problem between banks and depositors that leads to an endogenous leverage constraint, which, in turn, limits the banks' ability to supply credit. The government sector issues lump-sum transfers to households, collects taxes from firms, and issues long-term bonds. Government bonds are risky because the government can default on these bonds. Following Bocola (2016), I assume that sovereign risk is an exogenous process, independent of the fundamentals of the economy. In the event of default, the government writes off part of its stock of debt, weakening banks' balance sheets and affecting the credit supply, which in turn leads to an increase in corporate risk. In addition to this endogenous bank-lending channel, and to match the total increase in corporate risk (as implied by the empirical estimates), I assume that a sovereign default leads to an exogenous productivity loss for the corporate sector. This efficiency cost captures, in a reduced-form way, all the other channels from which sovereign risk can affect corporate risk.[3]

The sovereign-to-corporate-risk channel described in the model affects the real economy in two different ways. On the one hand, an increase in sovereign risk leads to an increase in firms' default risk that reduces investment and the demand for credit. On the other hand, an increase in sovereign risk deteriorates banks' balance sheets, which reduces the supply of credit and further increases corporate risk. The increase in corporate risk further weakens banks' balance sheets, amplifying the macroeconomic effects of sovereign risk.

I show that the quantitative model is able to reproduce the size and persistence of the Italian recession, as well as the asymmetric response of corporate risk across firms with

[3] In Appendix C.2, I show that the Italian TFP is strongly correlated with the government default risk. Moreover, I find that the reduced-form productivity loss considered in the model leads to an expected present value of TFP similar to the one observed in the Italian data.

different levels of risk. Corporate risk plays a key role in the recession. In a counterfactual in which corporate risk is not affected by sovereign risk, I show that the contraction in the supply of credit explains only a small fraction of the drop in aggregate output. Once corporate risk is introduced, the model is able to generate a much larger drop in aggregate output. Although part of this drop is explained by the (exogenous) expectation of lower productivity upon a sovereign default, I show that the bank-lending channel accounts for almost 40% of the decline. Lastly, I show that corporate risk accounts for almost a third of the decline in banks' net worth. By further weakening banks' balance sheets, I find that the feedback between corporate risk and banks' net worth slows the speed of the recovery and increases the drop in aggregate output by 15%.

The heterogeneity of firms allows to decompose the effects by firms' risk, which is relevant for policy analysis. Consistent with the empirical findings, I show that riskier firms are significantly more affected by increases in sovereign risk. These firms reduce their investment more (relative to safer firms) and are also behind the decrease in banks' net worth. Through their effects on banks' balance sheets, riskier firms therefore indirectly affect safer firms, amplifying the effects of the crisis. I then study different policies that can mitigate the negative effects of an increase in sovereign risk. I identify efficiency gains from policies that exploit firms' heterogeneous reactions to increases in sovereign risk. In particular, I show that a debt relief program geared toward riskier firms has important spillover effects that operate through the bank-lending channel, benefiting safer firms with lower interest rates and a larger credit supply.

The model features several state variables including the firm distribution, an infinite-dimensional object, aggregate uncertainty, and occasionally binding constraints, which makes it challenging to solve. I follow a Krusell and Smith (1998) type of approach to approximate the firm distribution using a finite set of moments. I solve the model using global methods, and I use graphic processing units (GPUs) to highly parallelize the algorithm.

Related Literature. The paper relates to several strands of the literature. It combines elements of the empirical literature about the transmission of sovereign risk to the corporate sector with elements of the quantitative literature about the macroeconomic implications of sovereign risk.

The paper is closely related to the quantitative literature on the links between sovereign risk and the corporate sector through financial intermediation. The closest study is Bocola (2016), who poses a model in which news about a sovereign default decreases banks' net worth, limiting their ability to provide credit and affecting the real economy.[4] The

[4] Sosa-Padilla (2018) presents a similar framework but allows for endogenous sovereign defaults. Gennaioli et al. (2014) pose a more stylized model in which sovereign risk also affects banks' balance sheets and investment decisions. In Perez (2018), after a default, the government loses reputation and its ability to issue debt. The lower supply of sovereign debt leads banks to substitute away from government bonds to investments in less productive projects. Ari (2019) builds a model with multiple equilibria. In the "gambling equilibrium," banks do not cut down their exposure to government bonds after an increase in sovereign risk. This leads to an increase in banks' insolvency probability (which rises their funding

main difference with respect to this paper is that I allow for non-financial defaults, generating a two-way feedback loop between corporate risk and banks' net worth that is absent in Bocola's analysis. Arellano et al. (2019), Farhi and Tirole (2018), and Acharya et al. (2014) analyze different feedback mechanisms than the one presented in this paper. Arellano et al. (2019) analyze the feedback loop between aggregate output and sovereign risk. In their model, an increase in sovereign risk leads to lower output, which in turn further increases the government's default incentives. Similarly to this paper, they emphasize the role of firm heterogeneity behind their feedback mechanism. Farhi and Tirole (2018) and Acharya et al. (2014) focus on the feedback between sovereign risk and banks' bailouts. Lastly, Rojas (2020) considers a framework that also allows for sovereign risk and firms' default. The key difference from my setup is that he does not consider the effects of corporate risk on banks' net worth.

The paper also connects to the empirical literature on the pass-through of sovereign risk. Bottero et al. (2020), Kalemli-Ozcan et al. (2020), Bentolila et al. (2018), Bofondi et al. (2018), Buera and Karmakar (2018), and Cingano et al. (2016), among others, use bank- and loan-level data to measure the differential response in the credit supply of banks with different sovereign exposures during the last European debt crisis. They show that those banks with higher (pre-crisis) sovereign exposures reduced their credit supply significantly more.[5] I contribute to this strand of the literature showing that banks with higher sovereign exposures not only decreased their credit supply to the non-financial sector, but also experienced a larger increase in their corporate NPLs. The closest paper in this regard is Farinha et al. (2019), who quantify the likelihood of a corporate default for firms that are linked to banks with different degrees of sovereign exposure.

More generally, the paper is related to the sovereign literature that quantifies the transmission of sovereign risk to the real economy. The closest study in terms of methodology is Hébert and Schreger (2017), who exploit the legal rulings in the case *NML Capital v. Republic of Argentina* to isolate exogenous changes in sovereign risk. Although these legal rulings are an excellent source of exogenous variation, they represent a very particular set of events that makes their analysis difficult to validate in a different setting. An advantage of the analysis presented in this paper, therefore, is its external validity. The paper also expands on the literature that identifies the transmission of sovereign to corporate (and financial) risk (Augustin et al., 2018, Almeida et al., 2017, Adelino and Ferreira, 2016, and Acharya et al., 2014).[6] Finally, it is also connected to a strand of

costs) and to a larger drop in lending to the private sector.

[5]These studies also highlight the role of firm heterogeneity. They show that smaller firms, firms with higher leverage, and firms with shorter maturities were the most affected by the credit crunch.

[6]Almeida et al. (2017) identify this transmission by exploiting the asymmetric variation on corporate ratings that is due to rating agencies' sovereign "ceiling" policies. Adelino and Ferreira (2016) employ a similar strategy, but they focus on financial firms. Augustin et al. (2018) use the Greek bailout in April 2010 as an exogenous variation of sovereign risk and measure its effect on credit default swaps (CDS) of non-financial European firms. Using a similar methodology, Acharya et al. (2014) measure the spillover effects from sovereign risk into financial firms around the Lehman Brother's bankruptcy in 2008. The use of CDS implies that the firms in their datasets are tilted toward the largest European firms (even from the subsample of publicly traded firms). An advantage of the analysis presented in this paper is

the literature that uses a narrative approach based on news events to capture exogenous variation on sovereign risk (Bahaj, 2020, Beetsma et al., 2013 and Brutti and Sauré, 2015). Bahaj (2020), for instance, uses a narrative approach to identify exogenous shocks to sovereign risk and feeds those shocks to a VAR to study the macroeconomics implications of sovereign risk. Instead, I follow a more structural approach by posing a fully non-linear quantitative model. This is important in the context of my model because the amplification mechanism between sovereign and corporate risk leads to important nonlinearities.

The rest of the paper is organized as follows. Section 2 presents the empirical analysis on the transmission of sovereign to corporate risk. Section 3 studies the role of the bank-lending channel in that transmission. Section 4 describes the model. Section 5 presents the quantitative analysis. Section 6 concludes.

2 The Transmission of Sovereign to Corporate Risk

This section quantifies the causal effect of sovereign risk on the default risk of non-financial firms. Subsection 2.1 presents the dataset and describes the framework used to compute a high-frequency measure of corporate risk. In subsections 2.2-2.4, I present the identification strategy together with the description of the events, the heteroskedasticity-based framework, and the main results. Subsection 2.5 shows the heterogeneous effects across firms behind the transmission of sovereign risk. Subsection 2.6 analyzes the potential role play by common factors and discusses potential challenges to the identification strategy.

2.1 Data Sources and Construction of Corporate Risk

The analysis in this section uses Italian data to estimate the causal effect of sovereign risk on corporate risk. To measure corporate risk, I retrieve financial data for 120 publicly traded non-financial Italian firms. The firms included in the analysis are the constituents of the *DS non-financial Italian Index*. Data include daily information of stock prices and shares outstanding, annual balance-sheet variables, and other firm-level indicators such as industry and share of exports. I use these variables to compute a daily (unweighted) index for non-financial credit risk. I use 10-year credit default swaps (CDS) to measure changes in Italian sovereign risk. Finally, I use the daily changes in S&P 500 and VIX to account for global factors that may affect Italian sovereign and corporate risk at the same time. All these data come from Datastream.

To measure non-financial firms' default risk, I employ the distance-to-default (DD) framework developed by Merton (1974).[7] The key insight of this approach is to view the equity of a firm as a call option on the underlying value of the firm. While neither the value of the firm nor its volatility are directly observable, under the model's assumptions,

that it also includes "smaller" publicly traded firms that do not issue CDS.

[7]The distance-to-default framework has been used extensively in the literature. See for instance, Bharath and Shumway (2008), Gilchrist and Zakrajšek (2012), or Ottonello and Winberry (2020).

both can be inferred from the value and volatility of the firm's equity and capital structure (Gilchrist and Zakrajšek, 2012). The main advantage of using this measure, instead of corporate CDS, is that the latter are only available for the largest firms, even from the pool of publicly traded firms (Subrahmanyam et al., 2014).

The Merton DD model makes two key assumptions. The first one is that the value of a firm (V) follows a geometric Brownian motion:

$$\frac{dV}{V} = \mu_V dt + \sigma_V dW \tag{2.1}$$

where μ denotes the expected continuously-compounded return on V, σ_V is the volatility of the process, and dW is a standard Wiener process. The second assumption is that the firm has issued only one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firms' debt (D).

From the Black-Scholes-Merton option-pricing, the value of the firm's equity satisfies:

$$E = V\Phi(\delta_1) - e^{-rT} \times D\Phi(\delta_2) \tag{2.2}$$

where $\delta_1 \equiv \frac{1}{\sigma_V\sqrt{T}}\left(ln(V/D) + (r + 0.5\sigma_V^2)T\right)$, $\delta_2 \equiv \delta_1 - \sigma_V\sqrt{T}$, $\Phi(.)$ denotes the cdf of the standard normal distribution, and r is the risk-free rate. Using the two previous equations and Ito's lemma, the relation between the volatility of the firm's value and the volatility of its equity is given by:[8]

$$\sigma_E = \frac{V}{E}\Phi(\delta_1)\sigma_V \tag{2.3}$$

Notice that the face value of debt D can be directly observed from the firm's balance sheet data. E can be easily computed by multiplying the firm's shares outstanding by its current stock price and σ_E can be estimated using historical returns data. We can therefore solve equations (2.2) and (2.3) to map these observed variables into the unobserved components V and σ_V.[9] After we solve for these two variables, the distance to default can be computed as:

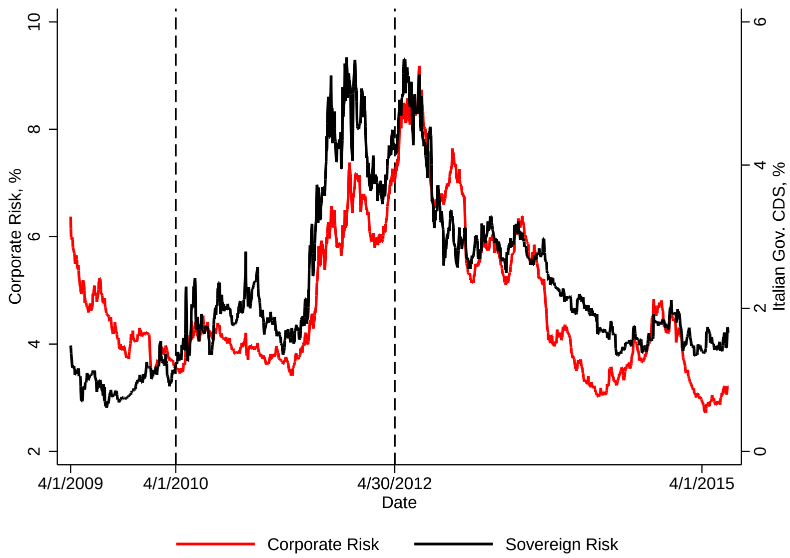
$$DD = \frac{ln(V/D) + \left(\mu_V - 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{2.4}$$

Under this framework, default occurs whenever $V/D < 1$. The Merton's DD can therefore be interpreted as the number of standard deviation the log of this ratio must deviate from its mean for a default to occur. The measure of corporate risk, i.e. the implied probability of default, is given by $CR \equiv \Phi(-DD)$. If all the assumptions of

[8] Here, I use the fact that, in the Black-Scholes-Merton model, $\frac{\partial E}{\partial V} = \Phi(\delta_1)$.

[9] As shown by Vassalou and Xing (2004), market leverage V/E typically displays a large degree of volatility which may lead to large swings in the volatility σ_V. To overcome this problem, I follow the iterative procedure proposed by Bharath and Shumway (2008). First, I start the recursion with an initial condition for σ_V and use equation (2.2) to solve for V. Second, I compute the daily log-return on assets (ΔlnV) and use that series to estimate μ_V and σ_V, following equation (2.1). Third, I update the value of σ_V accordingly until convergence is reached.

Figure 2.1: Italian Sovereign and Corporate Risk



Notes: Figure shows measures for Italian sovereign and corporate risk. Black line depicts the 10-year Italian government credit default swaps (CDS). Red line shows the unweighted average of the non-financial credit risk measure, based on Merton's distance-to-default framework.

the Merton model hold, CR is a sufficient statistic for predicting default (Gilchrist and Zakrajšek, 2012).

Figure 2.1 plots the (unweighted) average of CR for the panel of publicly traded Italian firms together with the Italian government CDS. As clearly shown in the figure, there is a strong positive correlation between sovereign risk and Merton's measure of corporate risk. In particular, between April 2010 (first Greek bailout) and April 2012, both measures increased sharply. In the next subsection, I study to what extent the increase in corporate risk was caused by the increase in sovereign risk.

2.2 Identification Strategy

The key challenges to the identification of the causal link of sovereign risk on corporate risk are: (i) sovereign risk may increase in response to deteriorating economic fundamentals that lead to an increase in corporate risk; and (ii) unobserved common shocks may be behind the increase in both sovereign and corporate risk.

The identification strategy relies on a narrative approach based on a set of "foreign news events". The identifying assumption is that these news events do not directly affect Italian fundamentals but are likely to affect Italian sovereign risk through contagion. Contagion is defined as a largely unpredictable, higher correlation across countries during crisis times compared to normal times (Pesaran and Pick, 2004). This implies that a crisis in one country increases the likelihood of a crisis in another country over and above what would be implied by the interdependence that prevails between these countries in non-crisis times.[10] For instance, a crisis initially restricted to one country may lead investors to reassess the vulnerability of other countries, which spreads the crisis across borders. Ludwig (2014), Beirne and Fratzscher (2013), Giordano et al. (2013), Mink and de Haan (2013), and Kalbaska and Gatkowski (2012), among others, have shown the presence of sovereign contagion during the last European debt crisis, either in the form of "pure contagion" or "wake-up-call".[11]

The set of "foreign news events" are based on news from two European countries: Greece and Portugal. The events include news about credit-rating downgrades for these two countries as well as news about bailouts between April 2010 and April 2012. Appendix A.1 lists and describes all the events considered. The assumption is that these foreign news events affected Italian corporate risk only through the effect on the Italian government default probability. In other words, these events capture exogenous shocks to the Italian government default probability and, therefore, allow to identify the causal link of sovereign risk on corporate risk. There are four underlying assumptions behind this identification strategy, which are analyzed below.

The first assumption is that the news events are not driven by Italian fundamentals. For instance, the decision by Moody's or some other risk agency to downgrade the sovereign credit rating of Greece or Portugal does not depend on the underlying fundamentals of the Italian economy. This is a sensible assumption given the methodology followed by credit rating agencies (see, for instance, Bhatia, 2002). In this same way, it is assumed that ECB and IMF decisions about a bailout package for Greece or Portugal are not influenced by Italian fundamentals.

The second assumption is that Italian firms are not directly affected by these news events, apart from the effect through the change in Italian sovereign risk. This is a reasonable assumption as (i) exports to Greece and Portugal represent less than 3% of the Italian exports; (ii) imports from Greece or Portugal represent 1% of the Italian imports; (iii) the exposure of Italian banks to Greek and Portuguese sovereign debt represent less than 1% of their entire sovereign exposure (which accounts for less than 0.1% of their assets); and (iv) Italian firms do not borrow from banks domiciled in Greece or Portugal.

[10] Contagion, therefore, excludes spill-overs effects across countries that are driven by countries links, such as trade or investment flows. See Masson (1998) for a general categorization of the different mechanisms through which crises spreads across countries.

[11] Ludwig (2014) provides a decomposition of contagion between "pure contagion" and "wake-up-call contagion". Beirne and Fratzscher (2013) and Giordano et al. (2013) provide evidence consistent with "wake-up-call contagion". They show that until the Greek crisis, investors partially ignored macroeconomic indicators when pricing Euro-area sovereign bonds. During and after the crisis, they show that financial markets have become more sensitive to countries' fundamentals. Mink and de Haan (2013) find evidence suggesting that the news about the Greek bailout provided a signal to investors about the European government's willingness to use public funds to combat the financial crisis and this signal affected other Euro-area countries spreads. Kalbaska and Gatkowski (2012) show a significant rise in cross-country interdependencies after the global financial crisis as compared with the pre-crisis periods, consistent with the definition of contagion. Arellano et al. (2018) pose a model in which contagion in sovereign risk arises because countries borrow from common international lenders.

Tables A.5-A.7 in Appendix A.2 provide the supporting evidence.

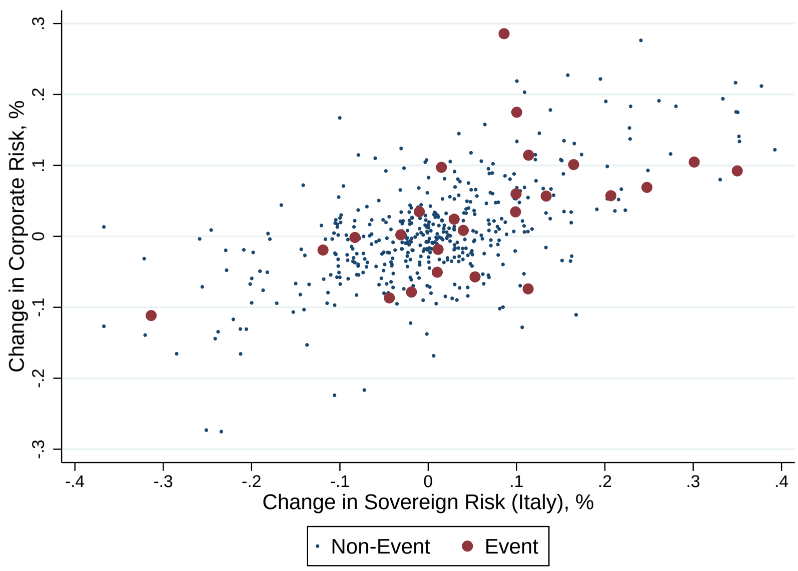
The third assumption is that (potentially unobserved) common factors around the event days, such as a change in the market price of risk, do not lead to a simultaneous increase in both sovereign and corporate risk across Europe. In subsection 2.6, I provide evidence supporting this assumption, by comparing the outcomes of European countries that were not severely affected by the sovereign debt crisis (Germany and France, for instance).

The fourth, and last, assumption is that the market does not fully anticipate the foreign news events. If it does, then the listed events are not suitable to capture exogenous variation in sovereign risk. As investors may have partially anticipated some of these news (particularly news regarding sovereign downgrades), I show that results are robust to an alternative (endogenous) definition of events based on the volatility of Greek CDS.

2.3 Summary of Events

Figure 2.2 plots the daily change in the 10-year Italian government CDS versus the daily change in Italian corporate risk. Smaller dots represent non-event days while the larger red dots are for the foreign news event days. The figure shows a clear positive correlation between sovereign and corporate risk during the event days. Table 2.1 shows summary statistics, during a symmetric three-day event and non-event windows. Appendix A.3 presents the same figures for other European countries.

Figure 2.2: Italian Corporate Risk vs Italian CDS



Notes: Figure shows the daily change in the 10-year Italian government CDS and the daily change in Italian corporate risk. The latter is based on the Merton distance-to-default framework and it corresponds to the unweighted average across all the firms in the sample. Sample period: April 2010 - April 2012.

Table 2.1: Summary Statistics

Moment	Non-event	Event
Mean ΔCDS_t(percent)	0.0012	0.0246
Mean ΔCR_t(percent)	0.0046	0.0086
SD ΔCDS_t(percent)	0.1297	0.1837
SD ΔCR_t(percent)	0.0867	0.0920
$cov(\Delta CDS_t, \Delta CR_t)$	0.0065	0.0113
Number of Days	416	77
Number of Events	-	29

Notes: The table reports the mean and standard deviation of the daily change in the 10-year Italian government CDS, the mean and standard deviation of the daily change in the (unweighted) average corporate risk for Italian firms, and their covariance, during the event and non-event windows. Corporate risk is based on the Merton distance-to-default framework. Event-window days are defined as the 3-day symmetric window around the "news" days. Non-event days are all the others. Sample period: April 2010 - April 2012.

2.4 Framework and Results

In this section, I estimate the causal effect of sovereign default risk on corporate risk. The analysis presented here follows closely the work by Hébert and Schreger (2017). To allow for the possibility that (i) Italian sovereign risk may have increased in response to an increase in corporate risk, and (ii) unobserved common factors, I consider the following system of equations:

$$\Delta CR_t = \alpha_0 + \alpha_1 \Delta SR_t + \alpha_2 X_t + \epsilon_t \tag{2.5}$$

$$\Delta SR_t = \beta_0 + \beta_1 \Delta CR_t + \beta_2 X_t + \eta_t \tag{2.6}$$

where ΔCR_t is the change in corporate risk (based on Merton's distance-to-default measure), ΔSR_t is the change in sovereign risk (based on the Italian government CDS), X_t is a vector of (potentially unobserved) factors that affect both sovereign risk and corporate risk, ϵ_t is a shock to corporate risk, and η_t is a shock to sovereign risk. Our coefficient of interest is α_1, which captures the impact of sovereign risk on corporate risk.

If we simply run OLS in equation (2.5), there are two sources of bias: simultaneity and omitted variable bias. The former emerges if $\beta_1 \neq 0$, while the latter is present as long as $\alpha_2 \neq 0$ and $\beta_2 \neq 0$. In other words, the OLS estimate of α_1 is unbiased if corporate risk has no direct effect on sovereign risk and there are no omitted common shocks along the entire period under analysis. None of these assumptions seem valid in the Italian context. The four identifying assumptions described in the previous subsection are equivalent to the requirement that, during the event days, (i) the foreign news shocks are exogenous in the sense that η_t is not correlated with other shocks, neither with other lagged variables; and (ii) the exclusion restriction is satisfied: η_t affects ΔCR_t only through its effect on ΔSR_t.

I employ a heteroskedasticity-based identification strategy (Rigobon and Sack, 2004) around the foreign news events. The methodology is based on the (weaker) identifying assumption that the variance of the shocks to Italian sovereign risk is higher around the news events, whereas the variance of the shocks to corporate risk and other common factors remains the same. Let E denote the event-window days (as defined in Table 2.1) and let N denote all the other days. The approach imposes the following assumptions on the second order moments:

$$\begin{aligned} \sigma_{\eta,E} &> \sigma_{\eta,N} \\ \sigma_{\epsilon,E} &= \sigma_{\epsilon,N} \\ \sigma_{X,E} &= \sigma_{X,N} \end{aligned} \tag{2.7}$$

where $\sigma_{\eta,j}, \sigma_{\epsilon,j}, \sigma_{X,j}$ represent the standard deviation of the shocks and common factors across event and non-event days. Notice that this identification strategy does not rely on the complete absence of common and idiosyncratic shocks during the event windows.[12] Instead, it only requires the variances of the common shocks (σ_X) and corporate risk shocks (σ_ϵ) to be the same during event and non-event days.

For each set of events, $j = \{E, N\}$, we can estimate the following covariance matrix between ΔCR_t and ΔSR_t:

$$\Gamma_j \equiv \begin{bmatrix} var_j(\Delta CR_t) & cov_j(\Delta CR_t, \Delta SR_t) \\ cov_j(\Delta CR_t, \Delta SR_t) & var_j(\Delta SR_t) \end{bmatrix} \tag{2.8}$$

The difference in the covariance matrices during events and non-event days can be written as (see Appendix A.4):

$$\Delta\Gamma \equiv \Gamma_E - \Gamma_N = \lambda \begin{bmatrix} \alpha_1^2 & \alpha_1 \\ \alpha_1 & 1 \end{bmatrix} \tag{2.9}$$

where:

$$\lambda \equiv \left(\frac{1}{1-\alpha_1\beta_1}\right)^2 \left[\sigma^2_{\eta,E} - \sigma^2_{\eta,N}\right] \tag{2.10}$$

From equation (2.9), it is clear that we can estimate our coefficient of interest in (at least) two different ways:

$$\hat{\alpha}_1 = \frac{\Delta\Gamma_{12}}{\Delta\Gamma_{22}} = \frac{cov_E\left(\Delta CR_t, \Delta SR_t\right) - cov_N\left(\Delta CR_t, \Delta SR_t\right)}{var_E\left(\Delta SR_t\right) - var_N\left(\Delta SR_t\right)} \tag{2.11}$$

$$\tilde{\alpha_1} = \frac{\Delta\Gamma_{11}}{\Delta\Gamma_{12}} = \frac{var_E\left(\Delta CR_t\right) - var_N\left(\Delta CR_t\right)}{cov_E\left(\Delta CR_t, \Delta SR_t\right) - cov_N\left(\Delta CR_t, \Delta SR_t\right)}$$

Rigobon and Sack (2004) show that these estimators are consistent even if the shocks have heteroskedasticity over time. They also show how these estimators can be implemented in an instrumental variables framework. As explained in Hébert and Schreger

[12] This would be the assumption of an event study framework, as in Cook and Hahn (1989), Bernanke and Kuttner (2005), and many others.

Table 2.2: Sovereign Risk and Corporate Risk

	Dependent Variable: ΔCR_t			
	IV	OLS	IV	OLS
ΔSR_t	0.288***	0.3667***	0.2903***	0.3739***
95% CI	[0.120, 0.439]	[0.290, 0.436]	[0.155, 0.411]	[0.319, 0.432]
Controls	No	No	Yes	Yes
Events	29	-	29	-
Obs	486	486	469	469

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t). Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Events are the ones described in subsection 2.3. Controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

(2017), under the null hypothesis $\Delta\Gamma_{12} = 0$ so the $\tilde{\alpha}_1$ estimator is not appropriate.[13] In what follows, all the results are based on the $\hat{\alpha}_1$ estimator. As it can be viewed from equation (2.9), this IV instrument is relevant only under the assumption that $\lambda > 0$. Appendix A.5 shows that we can reject the null hypothesis $\lambda = 0$ based on two different tests for differences in variance.

Table 2.2 presents the estimates for the Rigobon and Sack IV instrument and, as a comparison, the (biased) OLS estimates. When indicated, daily changes in the S&P 500 and VIX indexes are included as global controls. If the three identifying conditions in equation (2.7) hold, controlling for these factors is not necessary. Nevertheless, they may be important in the case that common shocks do in fact play an important role.[14] The results indicate that every 1pp increase in the 10-year Italian CDS spreads leads to a 0.29pp increase in corporate risk.[15] During the second and third quarters of 2011, for instance, sovereign risk increased 3.75pp while corporate risk increased 3.15pp. Linearly extrapolating the estimates of Table 2.2, sovereign risk can therefore account for a third of the total increase in corporate risk.

2.5 The Role of Firm Heterogeneity

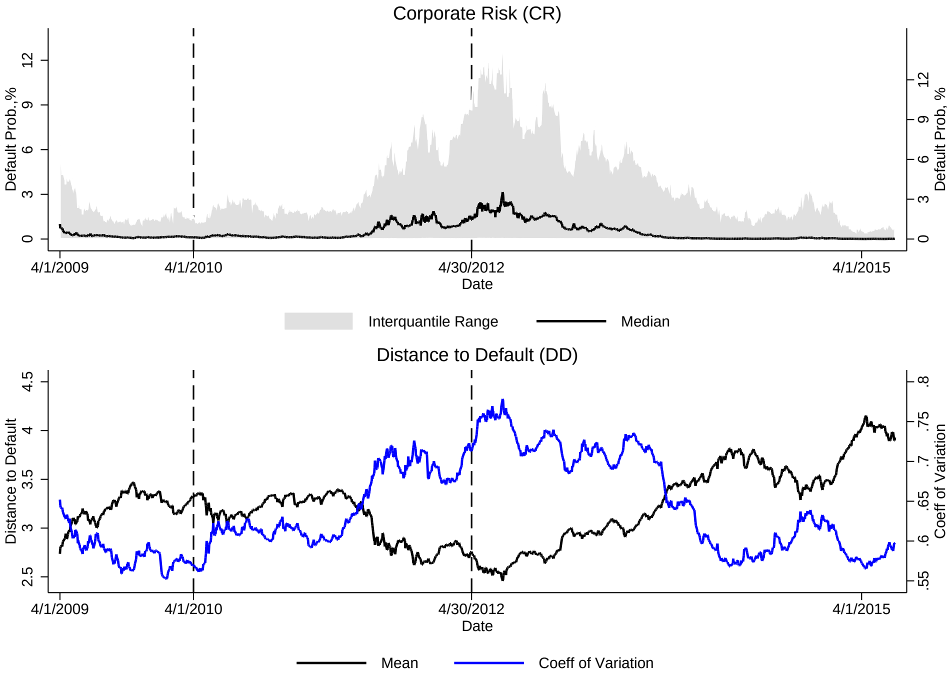
This section describes important asymmetric effects across firms behind the transmission of sovereign to corporate risk. The top panel of Figure 2.3 shows the evolution of Italian corporate credit risk for different percentiles of the distribution. As the crisis evolves, there is not only an increase in the median default risk, but also in its dispersion, as

[13] See Appendix A.7 for additional details.

[14] As shown in Table 2.2, the estimates are similar with or without these controls. I further explore the role of common factors in subsection 2.6.

[15] The estimates are in line with those reported by Augustin et al. (2018) and Acharya et al. (2014).

Figure 2.3: Heterogeneous Transmission

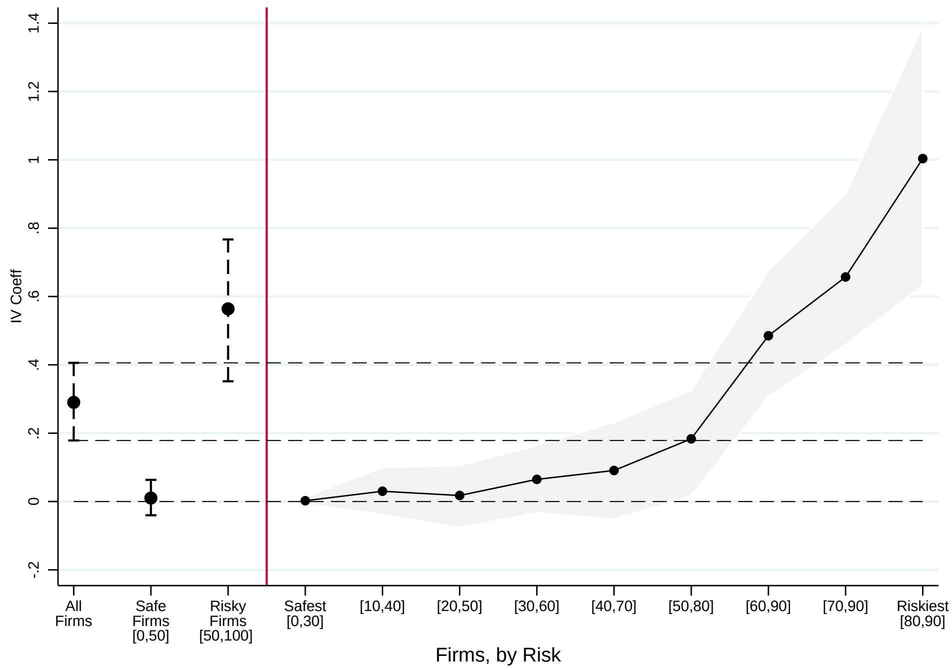


Notes: Top panel shows evolution of Italian corporate credit risk (based on Merton's DD framework) for different percentiles of the distribution. Black line depicts the median default probability, while the gray area represents the 25th-75th interquartile range. Bottom panel shows the average Merton's distance to default (black line), as defined in equation (2.4), and its coefficient of variation (blue line).

shown by the increase in the interquartile range. As corporate risk is bounded below by zero, it may be reasonable to expect an increase in its dispersion as the median value increases. The bottom panel of Figure 2.3, however, still shows a sharp increase in the coefficient of variation of the Merton's distance to default (which typically is larger than zero so it is not bounded) during the crisis.

While the analysis presented so far has focused on an aggregate measure of corporate risk, I show in Appendix A.6 how the system of equations in (2.5) and (2.6) can be easily extended to study the transmission of sovereign risk across different groups of firms. Under this extension, the Rigobon and Sack (2004) methodology still allows to identify the causal effect of sovereign risk on the corporate risk of each group. Using this approach, I sort firms into different bins, based on their pre-crisis average corporate risk (measured in 2009). For each of these bins, I apply the heteroskedasticity-based estimation procedure explained in Appendix A.6. Results are depicted in Figure 2.4. The figure shows that corporate risk of "safe" firms (those below the 50th percentile in terms of their pre-crisis risk) does not change significantly after the change in sovereign risk. As the firms' pre-crisis risk profile increases, the sensitivity of corporate risk to sovereign risk also increases. For instance, corporate risk for the set of "riskiest" firms increased one to one with respect to sovereign risk.

Figure 2.4: IV Coefficients, by Firms with Different Risk



Notes: The figure reports the results for the Rigobon and Sack (2004) IV estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t), for firms with different pre-crisis risk profiles. Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. The x-axis sorts firms across percentiles according to their pre-crisis risk profile in 2009. Events are the ones described in subsection 2.3. All the regression include changes in S&P 500 and the VIX index as global controls. Sample period includes April 2010 - April 2012. Grey area depicts the 90 percent confidence intervals, which are computed based on a percentile stratified bootstrap.

To control for potential firm characteristics driving the previous result, I consider a simple OLS panel regression that allows to control for firm-level factors. In particular, I consider the following first-difference regression model:

$$\Delta CR_{i,j,t} = \gamma_0 + \gamma_1 \Delta SR_t + \gamma_2 \left[\Delta SR_t \times CR_{i,j,2009}\right] + \gamma_3 X_{i,j,2009} + \gamma_4 \Omega_j + \gamma_5 Z_t + \epsilon_{i,j,t} \quad (2.12)$$

where $CR_{i,j,t}$ is the corporate risk of firm i, of industry j, at date t; $X_{i,j,2009}$ is a vector of (annual) firm controls (measured in 2009) that includes firm's size, leverage, and its share of foreign sales; Ω_j captures industry fixed effects; and Z_t is a vector of global controls. The coefficient of interest is γ_2 as the the focus is to establish whether corporate risk of riskier firms reacts more to changes in sovereign risk. The results in Table 2.3 suggest that even after controlling for many firm characteristics, those firms with higher pre-crisis risk seems to be more affected by the increase in sovereign risk. For the median firm, the estimates in column (3) show that a 1pp increase in the 10-year Italian CDS is associated with a 0.35pp increase in corporate risk. That increase is almost 0.55pp for a firm with a 12% pre-crisis default risk (firms above the 90th percentile). While this analysis does

Table 2.3: Dependent Variable: ΔCR

	(1)	(2)	(3)	(4)
Δ Italian CDS	0.3151***	0.3218***	0.3430***	0.3400***
	(0.0158)	(0.0162)	(0.0448)	(0.0260)
Δ Italian CDS $\times$ CR 2009	0.0173***	0.0180***	0.0175***	0.0133***
	(0.0034)	(0.0033)	(0.0034)	(0.0028)
Δ Italian CDS $\times$ log(Assets) 2009				0.0361**
				(0.0126)
Δ Italian CDS $\times$ Leverage 2009				0.9451***
				(0.2122)
Δ Italian CDS $\times$ Foreign Sales 2009				0.3102**
				(0.1107)
Observations	36,294	35,115	31,646	31,646
Global Controls	No	Yes	Yes	Yes
Firm Controls	No	No	Yes	Yes

Notes: Table presents OLS estimates of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk ($\Delta CR_{i,t}$) for a panel of publicly traded Italian firms. The variables log assets, leverage, and share of foreign sales are expressed as deviations from the 2009 mean across all the firms in the sample. Global controls refers to changes in S&P 500 and the VIX index. Column (3) refers to the specification in equation (2.12). Sample period includes April 2010 - April 2012. Standard errors are clustered at the industry level. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

not allow for a causal interpretation of the coefficients, it is still useful as it suggests that the IV estimates of Figure 2.4 are not driven by firm characteristics.[16]

Robustness

In appendix A.7, I conduct additional tests to asses the robustness of the results. Table A.9 shows that the results are robust to different specifications of the variables. In particular, the results are similar when the variables are measured as percentage changes (instead of absolute changes). Table A.10 shows that the results are robust to different subsets of events. For instance, the results are in line with the ones presented in the previous subsection if only bailout news are included as foreign news events. Lastly, Table A.11 shows that the results based on the $\tilde{\alpha_1}$ estimator (as defined in equation 2.11) are similar to the baseline estimates presented above.

A potential concern regarding the heterogeneous effects across firms is that the results may be driven by the different levels in pre-crisis corporate risk across firms. That is, given an increase in sovereign risk, the larger (absolute) increase in corporate risk across riskier firms may be simply explained by their larger pre-crisis value. To show that this

[16]The estimates of Table 2.3 can be interpreted as causal effects only under the complete absence of common factors and under the assumption that increases in individual corporate risk does not spill-over to a higher sovereign risk. In subsection 2.6, I present evidence in favor of common factors behind the pricing of sovereign and corporate risk. Moreover, given that the sample includes publicly traded firms (i.e., large firms), it is also likely to expect some spill-overs from corporate to sovereign risk.

is not the case, I repeat the same analysis but using the percentage change in Merton's distance to default (i.e., $\%\Delta DD$) as the dependent variable.[17] The results in Figure A.2 are in line with the ones described in the main text. That is, firms with higher pre-crisis corporate risk exhibit a larger percentage decrease in their distance to default.

2.6 Identification Challenges and Discussion

In this section, I discuss some challenges regarding the identification strategy. A potential concern about the results presented so far is the presence of common factors behind the increase in sovereign and corporate risk. While the Rigobon and Sack (2004) identification strategy does not assume the complete absence of common shocks, it requires the variances of these shocks to remain constant across event and non-event days. Therefore, if the foreign news events described in this paper lead to an increase not only in the volatility of Italian CDS but also in the volatility of common factors, the results presented in subsection 2.4 would be biased.

To explore the role of potential common factors, I start by analyzing if the results are driven by changes in the (volatility of) market price of risk across Europe. A change in the price of risk around the event days would lead to a simultaneous increase in both Italian sovereign and corporate risk, invalidating the identification assumption.

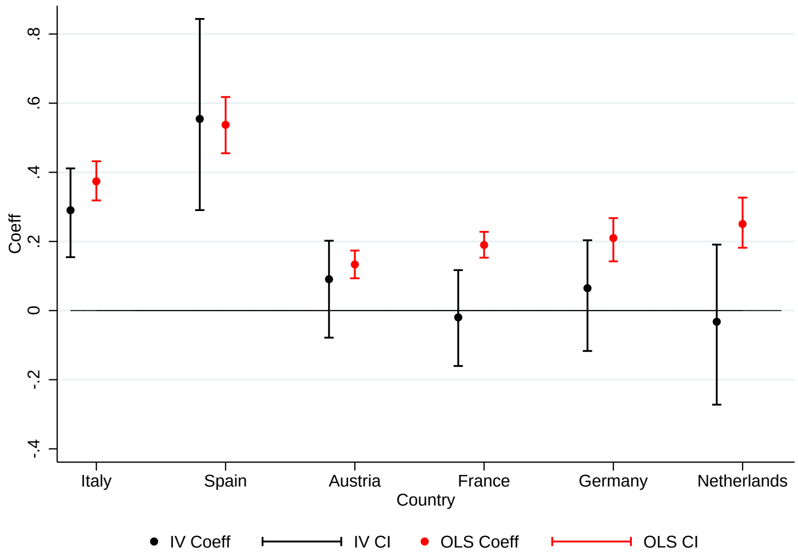
In the absence of cross-country market segmentation, if there is a change in the market price of risk, that change should be observed across Europe. Based on this observation, I apply the same Rigobon and Sack methodology for four other European countries that were not severely affected by the sovereign debt crisis: Germany, France, Austria, and the Netherlands.[18] For each of these countries, I construct a measure of corporate risk, following the same steps as the ones described in subsection 2.1, and I regress this measure to the change in the Italian government CDS. The results are depicted in Figure 2.5. The OLS estimates show a positive and significant relation for all the countries, indicating that the Italian sovereign risk co-moves with the non-financial default risk of European firms. The IV estimates, on the other hand, show that corporate risk in these countries does not respond to the foreign news events. We can interpret these results as evidence suggesting that there are common factors behind the pricing of corporate risk across Europe, but the foreign news events described in subsection 2.3 do not affect these common factors.[19] The analysis in Figure 2.5 also presents the OLS and IV estimates for Spain, a country severely affected by the European debt crisis. Not surprisingly, the IV estimates for Spain

[17]Working with $\%\Delta CR$ as the dependent variable is problematic given that, trivially, the biggest percentage changes are observed for the safest firms (whose pre-crisis corporate risk is close to zero). The $\%\Delta DD$ measure does not have this problem, as it is typically larger than zero.

[18]The increase in sovereign risk across these four countries was several orders of magnitude smaller than the one observed in GIIPS countries.

[19]This result is similar to the one presented in Hébert and Schreger (2017). Using the legal rulings in the case *NML Capital v. Republic of Argentina* as a source of exogenous variation, they find that changes in Argentina sovereign risk co-moves with other emerging market equity indexes (Brazil and Mexico), but they do not find a causal effect for these other markets.

Figure 2.5: IV and OLS Coefficients, by Country



Notes: The figure reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on Merton's measure of corporate risk (ΔCR_t), for six different European countries. Events are the ones described in subsection 2.3. All the regression include changes in the S&P 500 and the VIX index as global controls. Sample period includes April 2010 - April 2012. Vertical lines depict the 95 percent confidence intervals, which are computed based on a percentile stratified bootstrap.

are positive and significant, which indicates that the results presented in this study are not necessarily driven by the intrinsic characteristics of the Italian economy.

To further explore potential changes in the market price of risk across Europe, I analyze whether the option-implied volatility for an index of European industrial firms (STOXX 600 industrials index) is affected by the foreign news events (see Appendix A.8). The OLS estimates show that increases in Italian sovereign risk are associated with significant increases in the option-implied volatility of the index. In particular, a 1pp increase in Italian CDS leads to a 7.5% increase in the implied volatility. The Rigobon and Sack IV estimates, however, are not significant. The results suggest that changes in Italian sovereign risk are associated with changes in the market price of risk in Europe, but the foreign news events are not behind these changes.

A related concern is that there may be significant differences in pre-crisis levels of corporate risk across Europe. If Italian firms have, on average, a larger pre-crisis default risk relative to other European countries, the foreign news events may have a larger impact on Italian firms purely because of their higher pre-crisis risk, invalidating the previous analysis. In Appendix A.8, I show that this is not the case. In particular, I compare the Rigobon and Sack IV estimates for a subsample of Italian and German firms with similar pre-crisis levels of corporate risk. I show that even for firms with similar levels of risk, the

IV estimates are positive and significant for Italian firms but not significant for German firms.

The results may also be biased by the presence of global investors. While I have presented evidence showing no strong financial links between Italy and Greece and Portugal, it is still possible that global investors are exposed to both Greek or Portuguese sovereign debt and to Italian corporate firms. In that case, the exclusion restriction is violated as the foreign news events would not affect corporate risk only through the change in Italian sovereign risk.[20] To this end, I focus on a subset of "local" corporate Italian firms that are traded in the ISE (Italian Stock Exchange) but are not traded in any other foreign index. Arguably, these firms are less exposed to international investors and rely more on the domestic financial institutions. Table A.14 in Appendix A.8 presents the results, which are in line with the ones presented in Table 2.2, suggesting that global investors are not behind the results.

One of the underlying assumptions behind the identification is that the market does not fully anticipate the foreign news events. If it does, then the listed events are not suitable to capture exogenous variation in sovereign risk. As investors may have partially anticipated some of these news (particularly news regarding sovereign downgrades), I consider in Appendix A.8 an alternative definition of events based on the volatility of Greek CDS. In particular, I classify as foreign news events those days in which the 3-day rolling window standard deviation of the Greek CDS was higher than the 90^{th} percentile. Results reported in Table A.15 are in line with the ones presented in the main text suggesting that markets did not fully anticipate the foreign news events used in the analysis. A caveat of this endogenous identification of events is that changes in the volatility of Greek sovereign risk may potentially reflect changes in the underlying fundamentals of Italy (or, more broadly, Europe) that are transmitted to Greek sovereign bonds via contagion, making the identification analysis more problematic. Still, the analysis is important, as it shows that results are robust to using different specifications of the events.

Another potential problem with the identification strategy is that the foreign news events may coincide with credit-rating downgrades for Italy or with Italian government's policies that directly affect Italian corporate risk.[21] In Appendix A.7, I provide evidence against this concern by showing that the results are robust to the exclusion of dates in which the Italian sovereign credit rating was downgraded or in which the Italian government approved austerity packages. More generally, I also show that the results are robust to different subsets of foreign news events. In particular, I show that results are in line with the ones presented above when news about Portuguese bailouts are excluded, when only news about the first Greek bailout are included, or when news about both Greek

[20] Morelli et al. (2020), for instance, study the role of global banks in international lending. Focusing on the period around Lehman Brothers' collapse, they show that emerging-market bonds held by more-distressed global banks experienced larger price contractions.

[21] The exclusion restriction would only be violated if these downgrades or policies are unrelated to the change in Italy's default probability that is driven by the foreign news events. To the extent that those events are a response to the foreign news events, the identification strategy remains valid.

and Portuguese credit-rating downgrades are excluded. Overall, this analysis shows that the results are not driven by a particular subset of events which ameliorates the concerns that the estimates may be influenced by Italian news that coincide with the foreign news events.

Even when direct aggregate trade and financial links between Italy and Greece and Portugal are small (as described in Tables A.5 and A.6), it is possible that for some firms in the dataset those links are significantly larger. In that case, at the individual level, the variance of the shock to corporate risk may be higher around "news" events, violating the identifying assumption. Nevertheless, the results presented in this section use an unweighted average across 120 non-financial firms, making it reasonable to expect that the average exposure of the firms included in the sample is representative to the aggregate figures.

In terms of the interpretation of the results, even when the foreign news events do not depend on Italian fundamentals, it is plausible that the effects of these events do depend on the underlying fundamentals of the Italian economy. For example, the foreign news events may have a larger impact on corporate risk under a scenario in which the Italian fundamentals are deteriorated. The estimates presented in this analysis should therefore be interpreted as an average effect, across the different states of the economy. Even when the analysis is silent about a potential non-linear relationship between sovereign risk news, economic fundamentals, and corporate risk, the magnitude of the estimates presented emphasize the importance of the transmission of sovereign to corporate risk.

3 The Role of the Bank-Lending Channel

The analysis so far has shown that changes in sovereign risk lead to changes in corporate risk. The goal of this section is to study the role of the bank-lending channel behind this transmission. The underlying idea behind this channel is as follows. Upon an increase in sovereign risk, the net worth of a bank that is highly exposed to government's bonds decreases, limiting its ability to provide credit. When firms operating with this bank try to roll over their current loans, they may be required to meet higher credit standards (for instance, collateral), they may face a higher spread, or they simply will not be able to roll over their debt. These difficulties may induce more firms to default on their current loans, increasing corporate risk.

In this section, I use Italian bank-level data to quantify the role of the bank-lending channel in the transmission of sovereign risk to the corporate sector. While the previous section focuses on corporate risk for a sample of publicly traded firms (given the need of high-frequency data), in this section I use corporate non-performing loans (NPLs) for the universe of Italian firms as the measure of corporate risk. The results described in this section, therefore, are representative of the entire corporate sector and not only of the subset of publicly traded firms.

3.1 Data

Two different datasets are used. First, I use annual balance-sheet data for commercial, cooperative, and popular banks headquartered in Italy during the 2005-2013 period. The bank-level data comes from the *BilBank 2000* database distributed by ABI (the Italian Banking Association). The *BilBank* dataset is highly representative for the whole Italian banking sector. During 2008, for instance, total assets for the banks in the dataset accounted for 3,337 billion euros. According to aggregate data reported by the Bank of Italy, total assets for all monetary and financial institutions (MFIs) in Italy were 3,405 billion euros. The second dataset consists of Bank of Italy reports indicating, for each bank, the number of bank branches across regions as well as its headquarters location. The branches are reported at the commune level and I use this information to sort banks across the different Italian regions, which allows me to exploit within-region banks' heterogeneity across sovereign exposures. The main variables used in the analysis are banks' stock of NPLs, their sovereign exposure, size (as measured by log assets), share of loans, liquid assets, retail funding, net worth, profits, and reserves. Appendix B.1 describes how these variables are constructed and provides some summary statistics.

One of the major drawbacks of the *BilBank* dataset is that it does not provide a breakdown of sovereign bond holdings by country, so it is not possible to quantify the exposure to Italian bonds. However, as described in Table A.5, the data from the European Banking Authority (EBA) 2011 Stress Test show that, for five of the largest Italian banks, holdings of Italian sovereign debt represent around 85% of their total sovereign exposure. On this point, Kalemli-Ozcan et al. (2020) use detailed confidential ECB data and show that there is a strong home bias in sovereign holdings across European banks, as around 70% of a bank's government bond holdings consists of domestic bonds.[22] In the analysis that follows, I assume that all sovereign exposures are, in fact, domestic exposures.

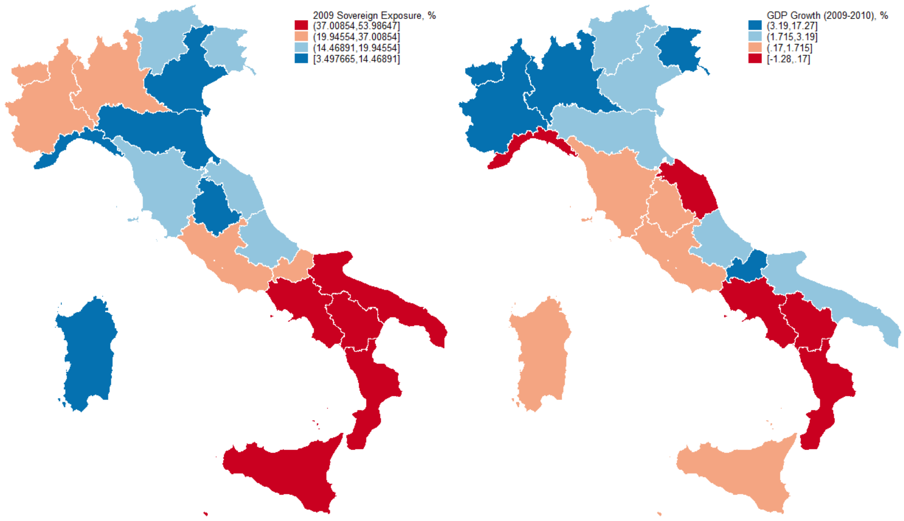
3.2 Identification Strategy and Analysis

I study next the role of the bank-lending channel behind the increase in corporate non-performing loans (NPLs). As the bank-lending channel is directly linked to the sovereign exposure of each bank, I exploit the heterogeneity across banks' pre-crisis sovereign exposures to measure this mechanism. The main challenge is to isolate the bank-lending channel from other (demand-driven) changes that may affect firms' NPLs. For instance, banks with higher pre-crisis sovereign exposures may have been lending to riskier firms, to firms or industries that were affected more during the crisis, or to firms located in the most affected regions.

To control for demand (firm-level) characteristics, the empirical literature on bank's sovereign exposure and its effects on credit supply (Bottero et al., 2020, Farinha et al.,

[22] Similarly, Gennaioli et al. (2018) document that bank's sovereign holdings exhibit a large home-bias. Arellano et al. (2019), also assume that the entire stock of government bond holdings across banks corresponds to domestic debt.

Figure 3.1: Italian Sovereign Risk and GDP Growth, by Region



Notes: Mean sovereign exposures by region. Italian five largest banks are excluded. Each bank is sorted into each region based on the location of its headquarters. Results are not weighted by bank size.

2019, Bentolila et al., 2018, Bofondi et al., 2018, Buera and Karmakar, 2018, and Cingano et al., 2016) typically follows the Khwaja and Mian (2008) methodology and runs *within-firm* difference-in-difference regressions. They focus on a subset of firms with two or more banking relations and explore the differential effect in the loans supplied to the same firm across banks with different sovereign exposures. This identification strategy allows to capture all the potential firm-level factors that may correlate with bank's sovereign holdings and changes in credit.

That type of study is out of the scope of the current paper as it requires loan-level data to match each firm with its lending bank. Instead, the analysis presented in this section relies on a simpler difference-in-difference framework that exploits within-region heterogeneity across banks to capture all the demand-level factors that operate at the regional level and analyze the differential growth rate of NPLs for banks with different sovereign exposures. Figure 3.1 shows the importance of controlling for regional factors. The left panel shows banks' sovereign exposures and the right panel depicts the 2009-2010 GDP change for each Italian region. At the regional level, there is a clear positive relation between sovereign exposures and the size of the recession. While part of the recession may have been driven by the larger sovereign exposure of the most affected regions, several other factors (potentially correlated with the sovereign exposure, such as the risk profile of the banks) may have played a role. If anything, the figure calls for the importance of controlling by regional-level factors.

To capture these regional-level factors, banks are sorted across the 20 Italian regions

Table 3.1: Summary Statistics, by Region

Variable	Region				
	NW	NE	Central	South	Islands
Branches (sum)	17,482	17,170	9,639	7,139	3,473
Log Assets	14.20	12.98	13.12	12.38	12.28
Sovereign Exposure	0.169	0.140	0.175	0.339	0.305
NPLs/Loans	0.027	0.052	0.041	0.051	0.060
NPLs/Loans (non-fin firms)	0.030	0.062	0.047	0.061	0.072

Notes: Variables are measured at the end of 2008. Sovereign exposure is expressed in terms of banks assets. Non-performing loans are expressed in terms of banks loans. Table reports averages across banks (except for branches, for which the sum is reported). The five largest Italian banks are excluded. Results are not weighted by bank size.

based on the domicile of their headquarters, as reported by the Bank of Italy.[23] The underlying assumption is that there is a strong regional bias, in the sense that banks only lend to firms operating in their same region. For the remainder of the section, the five largest Italian banks (in terms of the assets reported in the ABI dataset) are dropped, as these are banks that operate across all the Italian regions.[24] Table 3.1 provides a breakdown of the main variables of interest across the five Italian macro-regions: North-West (NW), North-East (NE), Center, South, and Islands.[25] The table shows an important degree of heterogeneity across regions. For instance, banks in the South region are typically smaller banks that are significantly more exposed to sovereign bonds and exhibit a higher ratio of non-performing loans.

To explore the role played by banks' sovereign exposures in the increase in non-performing loans, I estimate the following first-difference regression model:

$$\%\Delta NPLS_{i,j,(2008+h)} = \beta_{0,h} + \beta_{1,h} SovExposure_{i,j,2008} + \beta_{2,h} X_{i,j,2008} + \gamma_j + \epsilon_{i,j,(2008+h)} \tag{3.1}$$

where $\%\Delta NPLS_{i,j,(2008+h)}$ measures the percentage change in NPLs for bank i, located in region j, between the base year (2008) and horizon h. I calculate a standardized growth

[23]The Italian regions are: Abruzzo, Basilicata, Calabria, Campania, Emilia-Romagna, Friuli-Venezia-Giulia, Lazio, Liguria, Lombardia, Marche, Molise, Piemonte, Puglia, Sardegna, Sicilia, Toscana, Trentino-Alto Adige, Umbria, Valle d'Aosta, and Veneto. If a bank reports more than one headquarter, it is classified based on the region in which the bank has more branches. Results are similar if banks are sorted into regions based on the number of branches of each bank.

[24]These banks are: Banca Nazionale del Lavoro, Banco Popolare, Intesa-Sanpaolo, Monte dei Paschi di Siena, and Unicredit. Arellano et al. (2019) follow the exact same approach.

[25]The composition is as follows: North-West: Piemonte, Valle d'Aosta, Liguria, and Lombardia. North-East: Trentino-Alto Adige, Veneto, Friuli-Venezia-Giulia, and Emilia-Romagna. Center: Marche, Toscana, Umbria, and Lazio. South: Campania, Abruzzo, Molise, Puglia, Basilicata, and Calabria. Islands: Sicilia and Sardegna.

rate for NPLs as follows:

$$\%\Delta NPLS_{i,j,(2008+h)} = \frac{NPLS_{i,j,(2008+h)} - NPLS_{i,j,2008}}{0.5 \times \left(NPLS_{i,j,(2008+h)} + NPLS_{i,j,2008}\right)} \tag{3.2}$$

This growth rate is bounded in the range $[-2, 2]$, which limits the influence of outliers.[26] The variable $SovExposure_{i,j,2008}$ measures bank's i exposure to sovereign debt at the base year; $X_{i,j,2008}$ is a vector of bank controls; and γ_j are region-fixed effects. The set of controls includes: bank size (as measured by log assets), share of loans, liquid assets, retail funding, net worth, profits, and reserves.[27] These controls are important because pre-crisis sovereign assets are not randomly assigned across banks (Bottero et al., 2020 and Gennaioli et al., 2018). In fact, holdings of government bonds are a function of bank characteristics, which may also be correlated with the riskiness of the bank's corporate loans.

If the increase in NPLs is correlated with unobservable firm-specific conditions that also correlate with banks sovereign exposure, the previous OLS specification would deliver a biased estimator for $\beta_{1,h}$, our coefficient of interest. For instance, the estimate would be biased if banks with higher sovereign exposure were systematically lending towards riskier firms that were affected more during the European debt crisis. More formally, the specification in (3.1) allows for unbiased OLS estimates of sovereign exposures on NPLs under three conditions:

(i) Parallel trend assumption: After controlling for the vector of covariates $X_{i,j,2008}$ and bank's region, the sovereign exposure must be uncorrelated with the risk-profile of its loans. In other words, if it weren't for the sovereign crisis, banks with higher sovereign holdings should display an increase in NPLs similar to those banks with lower exposure. While untestable due to the lack of an observable counterfactual, the results presented next are in line with this assumption, as they show that the estimate for $\beta_{1,h}$ is not statistically significant before the crisis.

(ii) Unexpected Shock: At the end of 2008, Italian banks should not have anticipated the European debt crisis and adjusted their portfolios accordingly. To put it differently, the perception of risk for sovereign holdings should not have changed in 2008. If this is not the case, then it seems plausible that banks adjusted the risk-profile of their loans in anticipation of the sovereign debt crisis, and the $\beta_{1,h}$ would capture this behavior. Acharya and Steffen (2015), Bottero et al. (2020), and Buera and Karmakar (2018), among others, provide evidence supporting this assumption.

(iii) Absence of firm-level factors: Given that the specification in (3.1) does not control for firm-level factors, in order to provide an unbiased estimate for $\beta_{1,h}$, it must be the case that regional-level factors capture all the unobservable firm-specific changes in credit

[26] Bottero et al. (2020) and Buera and Karmakar (2018) use the same standardization. Appendix B.2 shows the results for the log change in NPLs.

[27] It also includes the share of loans to non-financial firms when the dependent variable is NPLs of non-financial firms.

risk. For instance, to the extent that banks with higher sovereign exposure lend to firms or industries most affected by the crisis, this sorting should be captured at the regional level.

The third condition is the one that poses most restrictions and it is driven purely due to limitations of the dataset. On support of this assumption, Bottero et al. (2020) show that there is "no evidence of a systematic sorting" between highly exposed banks and the firms most affected by the crisis. In particular, their loan-level estimates with and without firm fixed effects are not statistically different. They conclude that "*the bias induced by firm-level demand is either nonexistent or relatively small.*" Similarly, on the relation between bank's exposure and loans during the crisis, Bofondi et al. (2018) show that "*results are quantitatively and qualitatively unchanged once we take into account observed and unobserved heterogeneity at the bank, firm, and time level. Similar results are indeed obtained when we plug firm fixed effects, which absorb all time-invariant observed and unobserved firm heterogeneity. The difference in the estimates is not large, suggesting that firm demand for credit does not play a very strong role.*" Farinha et al. (2019), Buera and Karmakar (2018), Bentolila et al. (2018), and Cingano et al. (2016) also show that firm-level factors do not play an important role in explaining the relation between bank's sovereign exposure and the contraction of credit during the last European crisis.

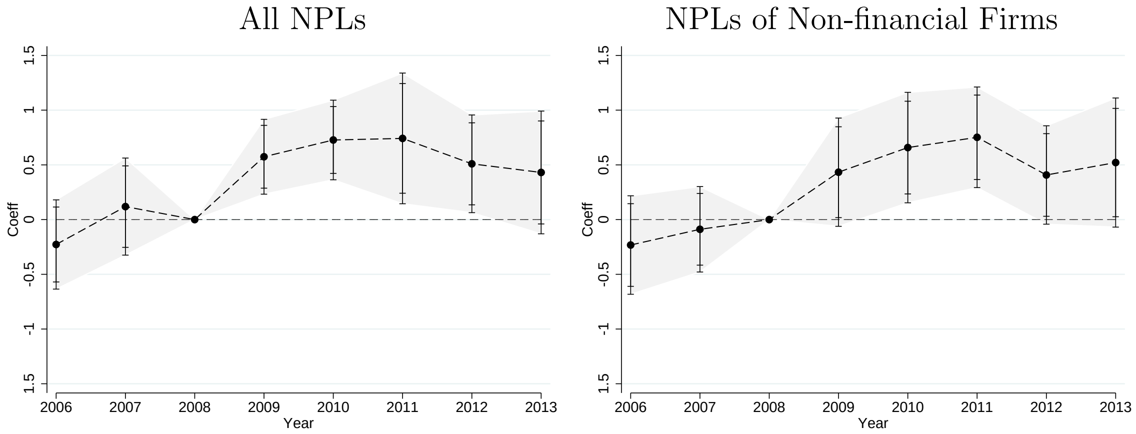
While these results suggest that regional-level factors may suffice to control for all the demand-level factors influencing NPLs, they are far from being a fully compelling argument. Due to the above limitations, the estimates of this section may not be interpreted as a causal estimate. Nevertheless, they are still useful as they highlight the fact that the bank-lending channel is an important driver behind the increase in NPLs.

3.3 Results

Figure 3.2 shows the OLS estimates and the 95 percent confidence interval for the $\beta_{1,h}$ coefficient in equation (3.1), for different horizons h. The left-hand-side panel shows the results for all NPLs (loans to firms and to consumers), while the right-hand-side panel focuses on the NPLs of non-financial firms. Before 2009, there are no significant differences in the growth rate of NPLs for banks with different sovereign exposure. The results are in line with the parallel trend assumption, in the sense that, before the sovereign crisis, exposures to government bonds were not associated with a faster increase of NPLs (after controlling for all the other bank characteristics). Since 2009, and particularly for 2010 and 2011, the results show a positive and significant relation between the 2008 sovereign exposure and the NPLs growth rate. The estimated coefficients imply that a 1 standard deviation increase in sovereign exposure is associated with a 15pp increase in the growth rate of NPLs. As NPLs increase about 80% during this period, the bank-lending channel can explain almost 20% of the observed increase.

Table 3.2 provides a further description of the estimates for the year 2011. Columns (2) and (5) correspond to the estimates plotted in Figure 3.2. Apart from the sovereign exposure, the bank's share of loans and its capital structure (particularly, its reserves)

Figure 3.2: Sovereign Exposure and NPLs



Notes: Figure reports the OLS estimates for the $\beta_{1,h}$ coefficient in equation (3.1). The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). To construct the CI, standard errors are clustered at the regional-level. The set of controls includes: bank size (as measured by log assets), loans, liquid assets, retail funding, net worth, profits, and reserves. For the right-hand-side panel, the share of loans to non-financial firms is also included as a control. Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks.

seem to be the main drivers behind the changes in NPLs. Columns (1) and (4) show the result when no regional dummies are included. As expected from the analysis in Figure 3.1, the magnitude of the estimates of $\beta_{1,h}$ are higher when these regional dummies are omitted, given the regional-level correlation between sovereign exposures and GDP growth. Finally, as banks may be operating across different regions and not only in the region where its headquarters are located, columns (3) and (6) report the OLS estimates for a broader level of aggregation of banks. In those columns, instead of sorting banks across the 20 Italian regions, each bank is sorted into one of the five Italian macro-regions (as defined in Table 3.1).[28] The estimates are in line with those associated to the finer aggregation level.

Altogether, the results presented in Figure 3.2 and Table 3.2 show that, even after controlling for many bank characteristics that capture the pre-crisis credit quality of their loan portfolios, a larger pre-crisis sovereign exposure is associated with a larger increase in corporate risk (as measured by corporate non-performing loans). The analysis, therefore, points out an important role of the bank-lending channel in the transmission of sovereign risk to the non-financial sector. Combined with the results presented in Section 2, the analysis implies an important amplifying mechanism of the pass-through of sovereign risk. That is, an increase in sovereign risk not only affects banks through their holdings of sovereign bonds, but also through the larger credit risk of their loans to non-financial firms, and the larger the sovereign exposure of the bank, the larger the increase in corporate risk. The goal of the quantitative model outlined in the next section is to quantify the real economic implications of this amplifying mechanism.

[28]Figure B.4 in Appendix B.2 plots the macro-region-level estimates for different horizons.

Table 3.2: Dependent Variable: %Δ NPLs

	(1)	(2)	(3)	(4)	(5)	(6)
		All NPLs			Non-financial NPLs	
Sov Exposure	0.8909***	0.7419**	0.8040**	0.9091***	0.7520***	0.8392**
	(0.2577)	(0.3046)	(0.2427)	(0.2689)	(0.2345)	(0.2767)
log(Assets)	0.0272	0.0141	0.0217	0.0262	0.0187	0.0253
	(0.0225)	(0.0274)	(0.0417)	(0.0221)	(0.0279)	(0.0330)
Net Worth	1.4316	1.6478	1.5434	0.5917	0.7350	0.6827
	(1.1758)	(0.9567)	(1.0583)	(1.2952)	(1.2533)	(0.9935)
Loans	1.4370***	1.5265***	1.5680**	1.1196**	1.1042***	1.2710**
	(0.4590)	(0.4628)	(0.4709)	(0.4594)	(0.3446)	(0.3103)
Retail Funding	0.5400	0.4367	0.4294	0.2739	0.2446	0.1435
	(0.3455)	(0.3207)	(0.3937)	(0.3293)	(0.2338)	(0.3648)
Profit	-0.3327	-1.8324	-1.9688	6.5305*	5.2966*	4.9362**
	(5.4085)	(4.8776)	(3.5719)	(3.4369)	(2.6862)	(1.7637)
Liquidity	1.0240	-1.0895	-0.2847	2.6379	-1.0332	0.8810
	(4.6689)	(4.8680)	(3.7687)	(5.4652)	(5.2978)	(3.9223)
Reserves	-5.1377***	-4.1392**	-4.7499**	-5.6849***	-4.5667***	-5.2472**
	(0.9916)	(1.4758)	(1.4641)	(0.9957)	(1.5070)	(1.2161)
Non-fin Loans				0.5348	0.7735	0.5129
				(0.3263)	(0.4730)	(0.3280)
Observations	425	425	425	419	419	419
Adjusted R^2	0.180	0.224	0.191	0.194	0.239	0.202
Region FE	No	Yes	Macro-Region	No	Yes	Macro-Region

Notes: The table reports the OLS estimators of the model in equation (3.1) for the 2011 year only. Dependent variable is the $\%\Delta NPLs$, as defined in equation (3.2). Sample excludes the five largest Italian banks. Columns (1) and (4) show the results when no regional dummies are included. Columns (2) and (5) sort banks into the 20 Italian regions, while columns (3) and (6) sort banks into the 5 Italian macro regions: North-West, North-East, Central, South, and Islands. Standard errors are clustered at the region-level (columns 2 and 5) and at the macro-region-level (columns 3 and 6). For columns (1) and (4), robust standard errors are computed. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

Robustness

I conduct different tests to asses the robustness of the results. All these results are reported in Appendix B.2. First, results are robust to alternative definitions of the dependent variable. Figure B.1 shows the results for the log change in NPLs, which is not bounded and therefore does not limit the influence of potential outliers. The estimated coefficients are in line with the ones presented in the main analysis (if anything they are slightly larger in magnitude). Figure B.2 presents the results when the dependent variable is given by the percentage change in the ratio of NPLs to bank's loans. Even for a bank whose NPLs do not increase during this period, this variable still captures a deterioration in the quality of the bank's portfolio to the extent that the bank reduced its credit supply. The magnitude of the estimates are slightly larger under this specification, consistent with the already documented fact that banks decreased their loans during this period.

Table B.2 shows that the results are robust to different specifications and to the addition of other bank controls (securities, bank funding, capital structure, and Tier 1). The analysis, moreover, highlights the importance of controlling for relevant bank-level factors that may correlate with both their sovereign exposure and the risk profile of their loans. Ignoring these controls leads to an insignificant relation between sovereign exposures and NPLs. Only after the vector of controls $X_{i,j,2008}$ is expanded to include variables describing the bank's assets, liabilities, and capital structure, the relation is positive and significant.

While the results in the main analysis show that the 2008 banks' sovereign exposures were not related to a larger growth rate of NPLs during the pre-crisis period (2006-2007), one could argue that this is not evidence in favor of the pre-crisis parallel trend assumption given that the aggregate growth rate of NPLs was relatively small during these years (so there is not a lot of dispersion across banks). To provide further evidence supporting this assumption, I repeat the same analysis but using 2007 as the base year. This exercise allows to shed some light on the validity of the parallel trend assumption because NPLs increased sharply during 2008 but Italian sovereign spreads did not increase until mid 2009. The results in Figure B.3 show that the growth rate of NPLs during 2008 is not related to the 2007 banks' holdings of sovereign debt, providing, therefore, evidence in favor of the identification assumption.

4 The Quantitative Model

I consider a model with incomplete markets and three sectors: a corporate sector formed by heterogeneous firms, a government, and households/bankers. There is a continuum of risk-neutral firms that are heterogeneous in their size, leverage and productivity. These firms hire labor and use their stock of capital to produce the unique final good of the economy. They can finance the purchases of capital using internal resources or by issuing debt in the form of long-term loans. Firms lack commitment and they can choose (or may be forced) to default on their stock of loans. There is also a government sector that issues lump-sum transfers to households, collects taxes from firms, and issues long-term bonds, which are also subject to default risk. All the credit in this economy is provided by the domestic bankers, which are owned by the households. Bankers use their net worth and households' deposits to finance their loans to firms and purchases of sovereign debt, and are subject to an agency problem that generates an endogenous leverage constraint.

Corporate risk is endogenously related to sovereign risk by the bank-lending channel. An increase in sovereign risk reduces the value of government debt, which in turn decreases banks' net worth. The lower net worth may trigger banks' leverage constraint, which leads to higher rates and a lower credit supply to the corporate sector. This, in turn, increases firms' default risk, which decreases banks' net worth even further. To match the total increase in corporate risk (as implied by the estimates of Section 2), there is an exogenous efficiency cost for the corporate sector in the event of a sovereign default. This efficiency cost exogenously captures all the other channels from which sovereign risk can affect corporate risk, such as trade, fiscal, or other general equilibrium effects that operate outside the bank-lending channel.[29]

4.1 Firms

There is a unit mass of heterogeneous firms that uses labor (l) and their own stock of capital (k) to produce the unique final good of the economy (y). Firms are risk-neutral, discount the future at rate β, and their objective is to maximize the present value of dividends. Firms' production is given by a decreasing returns-to-scale Cobb-Douglas technology:

$$y = (\xi z)^{[1-(1-\alpha)\times\chi]} \times \left(k^{\alpha} l^{1-\alpha}\right)^{\chi} \tag{4.1}$$

where χ rules the degree of decreasing returns in production, α is the value-added share of capital, ξ refers to the aggregate productivity, and z denotes the idiosyncratic productivity of the firm. This process follows a continuous Markov process:

$$log(z') = \rho_z log(z) + \sigma_z \epsilon_z \tag{4.2}$$

[29]See Borensztein and Panizza (2009) for a general discussion of different channels through which sovereign risk can affect the non-financial firms. Mendoza and Yue (2012) provide a microfoundation based on an imperfect substitution of imported inputs for domestic inputs. Kaas et al. (2020) provide a microfoundation based on taxes and Roldan (2020) focuses on aggregate wealth effects.

The aggregate productivity ξ only depends on the default status of the government and it is given by:

$$\xi = \begin{cases} 1 & \text{if Government is not in Default} \\ \xi_D < 1 & \text{if Government is in Default} \end{cases} \tag{4.3}$$

This variable captures productivity losses faced by firms in the event of a sovereign default and its purpose is to match the total increase in corporate risk. Even if the sovereign default is not realized, an increase in sovereign risk decreases firms' expected productivity which in turns leads to higher corporate risk.[30]

For a given choice of labor l, profits are given by: $\pi(l) = (1-\tau)[y(l) - w \times l]$, where τ is the proportional tax on firm's profit and w denotes the wage. To maintain computational tractability, I abstract from variation in wages and assume that they are constant. It is straightforward to show that the demand for labor is given by:

$$l(k,b,z) = \left[\frac{(1-\alpha)\chi \left[(\xi z)^{[1-(1-\alpha)\times\chi]} \right]}{w} \times k^{\alpha\chi} \right]^{\frac{1}{1-(1-\alpha)\chi}}$$

After replacing with the optimal amount of labor, we can write the profit function as follows:

$$\pi(k,b,z) = (1-\tau)\,\xi z k^{\gamma} \times \psi(w) \tag{4.4}$$

where: $\gamma \equiv \frac{\alpha\chi}{1-(1-\alpha\chi)}$ and $\psi(w) = \{1-(1-\alpha)\chi\} \left[\frac{(1-\alpha)\chi}{w}\right]^{\frac{(1-\alpha)\chi}{1-(1-\alpha)\chi}}$.

Incumbent firms can invest in capital and that accumulation process is subject to two frictions: (i) convex adjustment costs, and (ii) partial irreversibility. Let $\Delta(k',k') \equiv k' - (1-\delta)k$ denote the change in the stock of capital, where δ is the depreciation rate. The investment function is defined as:

$$I(k',k) = \begin{cases} \frac{\psi}{2}\left(\frac{\Delta(k',k)}{k}\right)^2 k + \Delta(k',k)\,P_+ & \text{if } \Delta(k',k) \geq 0 \\ \frac{\psi}{2}\left(\frac{\Delta(k',k)}{k}\right)^2 k + \Delta(k',k)\,P_- & \text{if } \Delta(k',k) < 0 \end{cases} \tag{4.5}$$

The expression $\frac{\psi}{2}\left(\frac{\Delta(k',k)}{k}\right)^2 k$ is a standard convex adjustment cost. The term $\Delta(k',k)\,P$, for $P = \{P_+, P_-\}$, typifies the partial irreversibility of capital, as in Abel and Eberly (1996). The assumption that $P_+ > P_-$ captures the notion of asset specificity and denotes that installed capital is less liquid than new capital. In the context of this model, P_- plays a crucial role when targeting the observed leverage ratios.

[30] In Appendix C.2, I show that, changes in Italy's TFP during the European debt crisis were tightly connected with Italian sovereign risk. Moreover, I show that the reduced-form productivity loss of equation (4.3) delivers paths of (expected) aggregate productivity that resemble the ones observed in the data.

Purchases of capital can be financed with internal resources (retained dividends) or by issuing debt in the form of long-term loans (b). Following Chatterjee and Eyigungor (2012), I consider long-term debt contracts that mature probabilistically. In particular, each unit of a loan matures next period with probability m_f and, if it does not mature, the firm has to pay a constant coupon c_f.[31] Firms lack commitment and they can choose (or may be forced) to default on their stock of loans. In the case of a default, the firm liquidates all of its assets and exits the industry forever (after production takes place). In the event of a default, the intermediaries (bankers) retrieve a fraction λ of the value of the firm. The recovery rate, per unit of loan, is given by:

$$R(k, b, z) = \lambda \times \frac{\pi(k, b, z) - I(0, k)}{b} \tag{4.6}$$

The firm's state space can be written as the n-tuple $(k, b, z; \boldsymbol{S})$, where $\boldsymbol{S}$ denotes the aggregate state, that includes the firm distribution, Ω. Let $q(k', b', z; \boldsymbol{S})$ denote the price of a unit of a loan for a firm with productivity z and whose next-period stock of capital and debt is (k', b'). Firm's dividends are given by:

$$d = \pi(k, b, z) - I(k', k) + q(k', b', z; \boldsymbol{S}) \times [b' - (1 - m_f)b] - [(1 - m_f) c_f + m] b \tag{4.7}$$

where the term $q(., \boldsymbol{S}) \times [b' - (1 - m_f)b]$ denotes the proceeds from issuing new loans and $[(1 - m_f) c_f + m_f] b$ denotes the current debt services.

For simplicity and to avoid modeling the equity issuance problem, I assume that firms are subject to a non-negative dividend constraint. This assumption implies that, if there is no combination of (k', b') that allows for $d \geq 0$ the firm must default.[32] Moreover, following Crouzet (2017), the firms also have an outside option available which depends on the firms' size. The recursive problem of an incumbent firm is given by:

$$\begin{aligned}
V(k, b, z; \boldsymbol{S}) = Max_{k', b'}\ \ & d + \beta \mathbb{E}_{(z', \boldsymbol{S}')|(z, \boldsymbol{S})} \left[max \left\{ V(k', b', z'; \boldsymbol{S}'), V^d(k', e_d') \right\} \right] \\
\text{subject to} & \\
& d = \pi(k, b, z) - I(k', k) + q(., \boldsymbol{S}) \times [b' - (1 - m_f) b] - [(1 - m_f) c_f + m_f] b \\
& d \geq 0 \\
& \boldsymbol{S}' = H(\boldsymbol{S})
\end{aligned} \tag{4.8}$$

where $V(k, b, z; \boldsymbol{S})$ denotes the firm's value function and $H(\boldsymbol{S})$ denotes the predicted law of motion for the aggregates and for the firm distribution, Ω. The firm's outside option takes the following specification:

$$V^d(k, e_d) \equiv a_d \times V\left(k, 0, \bar{z}; \bar{\boldsymbol{S}}\right) + \sigma_d e_d \tag{4.9}$$

[31] A unit loan of type (m, c) issued $t \geq 1$ periods in the past, has the same payoffs as another loan of the same type issued in period $\tilde{t} > t$. This means that we do not need to keep track of the history of loan issuances, simplifying the state space for each firm.

[32] Because debt is long-term, debt services represent a small fraction of firms' dividends. Therefore, only a very small share of firms default because they cannot guarantee non-negative dividends.

where $\bar{z}$ is the unconditional mean of the TFP process defined in equation (4.2) and $e_d \underset{iid}{\sim} N(0,1)$.[33] Given a realization for e_d, the firm's default policy can be defined as:[34]

$$\tilde{h}\left(k,b,z;\boldsymbol{S},e_d\right) = \begin{cases} 1 & \text{if } \{(k',b')\,:\,d\geq 0\}=\emptyset \text{ or } V\left(k,b,z;\boldsymbol{S}\right) < V^d\left(k,e_d\right) \\ 0 & \text{otherwise} \end{cases}$$

By integrating across the e_d shock, we obtain the share of defaulting firms for each idiosyncratic state: $h\left(k,b,z;\boldsymbol{S}\right) \equiv \int \tilde{h}(k,b,z;\boldsymbol{S},e_d)\phi(e_d)de_d$, where $\phi(e_d)$ is the pdf of a standard normal distribution. It is easy to show that:

$$h\left(k,b,z;\boldsymbol{S}\right) = \begin{cases} 1 & \text{if } \{(k',b')\,:\,d>0\}=\emptyset \\ 1-\Phi\left(\frac{V(k,b,z;\boldsymbol{S})-a_d\times V\left(k,0,\bar{z};\bar{\boldsymbol{S}}\right)}{\sigma_d}\right) & \text{otherwise} \end{cases}$$

In the event of a default, the firm exits the industry forever and it is replaced by a new entrant. For simplicity, the initial stock of capital and productivity for all the entrants are fixed. Let $\underline{k}$ denote the initial capital and let $\underline{z}$ denote the initial productivity. I assume that entrants do not have loans outstanding.[35]

4.2 Households

A household is composed of a fraction f of identical risk-neutral workers and a fraction $(1-f)$ of risk-neutral bankers with perfect consumption insurance among them. For simplicity, I assume that households do not value leisure and are willing to offer $\bar{l}>0$ hours of work at any given wage $w\geq 0$. As already mentioned, I assume that wages are fixed, hence firms' aggregate demand for labor, $\int l(.,\boldsymbol{S})d\Omega$, pins down the equilibrium level.[36] Moreover, to keep tractability, I assume that households are risk neutral and discount payoffs at rate $\tilde{\beta}>\beta$.

Households can save by making short-term deposits in banks. Let x denote households deposits and let $R_f(\boldsymbol{S})$ denote the risk-free interest rate. Each period, households receive

[33] For simplicity, I assume that the exit option $V^d(k,e_d)$ does not depend on the aggregate state, $\boldsymbol{S}$. In this way, I first solve a simplified version of the model without aggregate risk and use the value function of that problem, $V(k,b,z,\bar{\boldsymbol{S}})$, as the outside option in the model with aggregate risk. The notation $\bar{\boldsymbol{S}}$ is used to refer to the aggregate non-stochastic steady state.

[34] The timing assumption is that, at the beginning of the period and after observing all the idiosyncratic and aggregate shocks, the firm chooses whether to default or not. The default decision is taken before the optimal choice of next-period capital and loans.

[35] This assumption leads to similar results if we assume that a firm starts with no capital and an exogenous productivity $\tilde{z}$, and that the firm must take a loan to buy the (fixed) initial stock of capital $\tilde{k}$. Under this assumption, the initial stock of debt, $\tilde{b}$, is given by the solution to the following implicit equation: $\tilde{k}-q(\tilde{k},b,\tilde{z})\times b=0$ (if more than one solution exists, the lowest b is chosen).

[36] Wages are normalized to one and $\bar{l}$ is chosen so that there is never an excess demand for labor. At the price of w, there may be an excess of supply but I assume that wages cannot adjust to clear the market (i.e., there is unemployment).

lump-sum transfers from the government, $T(\boldsymbol{S})$, and banks' net proceeds, $\Pi(\boldsymbol{S})$. Their recursive problem is given by:

$$
\begin{aligned}
W_h(x,\boldsymbol{S}) &= Max_{c,x'}\ c + \tilde{\beta} W_h(x',\boldsymbol{S'}) \\
\text{subject to} & \\
& c + x'\frac{1}{R_f(\boldsymbol{S})} = wl(\boldsymbol{S}) + x + \Pi(\boldsymbol{S}) + T(\boldsymbol{S}) \\
& c \geq 0
\end{aligned} \tag{4.10}
$$

where $W_h(x,\boldsymbol{S})$ denotes the households value function. The Euler equation for the households implies that:

$$\beta R_f(\boldsymbol{S}) = 1 + \tilde{\mu}(\boldsymbol{S})$$

where $\tilde{\mu}(\boldsymbol{S})$ is the Lagrange multiplier associated with the non-negative consumption constraint. For the parametrization described in Section 5, this constraint never binds, which implies a constant risk-free interest rate, given by $R_f(\boldsymbol{S}) = R_f = 1/\tilde{\beta}$.

4.3 Bankers

Let η denote the bank's net worth after default decisions (from firms and the government) have been made. A banker uses its net worth η and households' deposits x' to issue loans to the firms and to buy government bonds. Bank's exit is stochastic, occurring with an exogenous probability $(1-\psi)$. A banker that exits becomes a worker and is replaced by a worker from his household.[37] In this sense, the share of types within each household is constant over time. Taking prices as given, the objective of the bank is to maximize the expected net worth η upon exit.

Similarly to Gertler and Karadi (2011), I introduce an agency problem between intermediaries and their depositors that limits banks' ability to supply credit. In particular, a banker can divert a fraction κ of its assets and transfer these resources to his household. In that case, the cost to the banker is that depositors can force the bank into bankruptcy and recover the remaining $1-\kappa$ fraction of assets. Under that scenario, for lenders to be willing to supply funds to the banker, the following incentive constraint must be satisfied:

$$\kappa\left(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\right) \leq W\left(\eta,\boldsymbol{S}\right) \tag{4.11}$$

where $\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega$ denotes the value of loans made to the non-financial firms, $q_B(\boldsymbol{S})B'$ is the value of the sovereign debt holdings (to be defined in subsection 4.4),

[37] An exiting bank transfers its net worth to its household. The entrant banker receives from the household and endowment of wealth to start operating. This transfer is equal to a fraction γ of the net worth of the exiting bank.

and $W(\eta, \boldsymbol{S})$ denotes the value function of a banker with net worth η. Bank's recursive problem is given by:

$$
\begin{aligned}
& W(\eta, \boldsymbol{S}) = Max_{x', B', b'(.)} \; \tilde{\beta}\mathbb{E}\left[(1-\psi)\,\eta' + \psi W(\eta', \boldsymbol{S}')\right] \\
& \text{subject to} \\
& \qquad \frac{1}{R_f}x' + \eta = \int q\left(., \boldsymbol{S}\right) b'(., \boldsymbol{S}) d\Omega + q_B(\boldsymbol{S})B' \\
& \qquad \eta' = -x' + \int \mathbb{R}_f(., \boldsymbol{S}')b'(., \boldsymbol{S})d\Omega + \mathbb{R}_G(\boldsymbol{S}')B' \\
& \qquad \kappa\left(\int q(., \boldsymbol{S})b'(., \boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\right) \leq W\left(\eta, \boldsymbol{S}\right) \qquad (4.12) \\
& \qquad \boldsymbol{S}' = H\left(\boldsymbol{S}\right)
\end{aligned}
$$

The first restriction represents the balance sheet of the bank. The second restriction is the law of motion for bank's net worth, which is a function of the deposits that the bank has to repay to households and the repayment of both the government and the firms. $\mathbb{R}_G(\boldsymbol{S}')$ denotes the next-period gross repayment per unit of government debt (to be defined in the next subsection) and $\mathbb{R}_f(., \boldsymbol{S}') \equiv \mathbb{R}_f(k', b', z'; \boldsymbol{S}')$ denotes the next-period gross repayment per unit of loan for each firm, which is defined as:

$$
\mathbb{R}_f(k, b, z; \boldsymbol{S}) \equiv \left[1 - h\left(k, b, z; \boldsymbol{S}\right)\right] \times M_f\left(k, b, z; \boldsymbol{S}\right) + h\left(k, b, z; \boldsymbol{S}\right) \times R\left(k, b, z\right)
$$

where $M_f(k, b, z; \boldsymbol{S}) \equiv (1 - m_f)\left(c_f + q\left(k', b', z; \boldsymbol{S}\right)\right) + m_f$, and $k' \equiv k'(k, b, z; \boldsymbol{S})$ and $b' \equiv b'(k, b, z; \boldsymbol{S})$ denote the firm's optimal policy functions.

It is easy to show (see Appendix C.1) that bank's value function is linear in net worth:

$$
W(\eta, \boldsymbol{S}) = \alpha\left(\boldsymbol{S}\right) \times \eta \tag{4.13}
$$

where:

$$
\alpha\left(\boldsymbol{S}\right) = \tilde{\beta}R_f\frac{\left[(1-\psi) + \psi\mathbb{E}\alpha\left(\boldsymbol{S'}\right)\right]}{1 - \mu(\boldsymbol{S})} \tag{4.14}
$$

and $\mu(\boldsymbol{S})$ is the Lagrange multiplier on the incentive constraint:

$$
\mu\left(\boldsymbol{S}\right) = Max\left\{1 - \frac{\tilde{\beta}R_f\left[(1-\psi) + \psi\mathbb{E}\alpha\left(\boldsymbol{S'}\right)\right]}{\kappa\left(\int q(., \boldsymbol{S})b'(., \boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\right)}\eta\,,\, 0\right\} \tag{4.15}
$$

The linearity of the value function implies that the heterogeneity in banker's net worth and in their loans across firms does not affect aggregate dynamics. Therefore, without loss of generality, it is sufficient to keep track of the aggregate net worth, N.

4.4 Government

Each period, the government gives lump-sum transfers to households, $T(\boldsymbol{S})$, and collects taxes from firms (based on the proportional tax on profits, τ), subject to the following exogenous fiscal rule:

$$\begin{aligned} PS(\boldsymbol{S}) &\equiv \tau \int \pi(k, b, z; \boldsymbol{S}) d\Omega - T(\boldsymbol{S}) \\ &= f_B^0 + f_B^1 \times B \end{aligned} \tag{4.16}$$

where $PS(\boldsymbol{S})$ denotes the government primary surplus and B denotes the stock of government bonds outstanding. Equation (4.16) implies that, for a given tax revenue, $\tau \int \pi(k, b, z; \boldsymbol{S}) d\Omega$, the government adjusts its lump-sum transfers to households based on its stock of bonds outstanding. This assumption is merely for computational tractability as it allows to pin down the government's surplus (deficit) based on only one variable (B), instead of depending on the entire distribution of firms.[38]

Government bonds are risky and the government can default on them. As for the firms, I model the government's long-term bonds following Chatterjee and Eyigungor (2012). Let m_G denote the fraction of government bonds that mature in any given period and let c_G denote the coupon payment. Let $h_G = \{0, 1\}$ denote the government's default status. If the government is not in default, $h_G = 0$, its budget constraint is given by:

$$q_B(\boldsymbol{S}) \times [B' - (1 - m_G) B] + PS(\boldsymbol{S}) = [(1 - m_G) c_G + m_G] \times B \tag{4.17}$$

In the event of default, the government writes off its entire stock of debt up to a lower limit $\underline{B} \leq B$.[39] While in default, it cannot issue new debt, nor it has to pay debt services.[40] Moreover, at the beginning of each period, the government exits default with probability ζ. Based on these assumptions, the government's gross repayment per unit of debt is given by:

$$\mathbb{R}_G(\boldsymbol{S}) \equiv [1 - h_G(\boldsymbol{S})] \times M_G(\boldsymbol{S}) + h_G(\boldsymbol{S}) \times q_B(\boldsymbol{S}) \frac{\underline{B}}{B}$$

where $M_G(\boldsymbol{S}) \equiv (1 - m_G)(c_G + q_B(\boldsymbol{S})) + m_G$.

[38] Another advantage of this setup is that f_B^1 can be chosen to avoid having explosive paths in the dynamics of government debt. Upon an increase in B, a value of $f_B^1 > 0$ sufficiently large leads the government to increase its primary surplus, decreasing the need of issuing additional debt.

[39] Modeling writes offs this way allows to simplify the state space as it is only necessary to keep the government's current default status as a state variable.

[40] To satisfy its budget constraint while in default, the government adjusts households' transfers so that $PS(\boldsymbol{S}) = 0$. The assumption has limited effects on aggregate dynamics because transfers are lump-sum.

Assuming that the government is not in default, the next-period default status is:[41]

$$h'_G = \begin{cases} 1 & \text{if } \epsilon'_h < s \\ 0 & \text{otherwise} \end{cases} \tag{4.18}$$

where ϵ'_h is a standard logistic random variable and s is a latent state that can be interpreted as the government's sovereign risk. For simplicity, even if part of the increase in sovereign risk could be attributable to the economy's fundamentals, I assume that the process governing the evolution of s is exogenous and independent of the economy's fundamentals. It follows a simple AR(1) process given by:[42]

$$s' = (1-\rho_s)\, s^{\star} + \rho_s s + \sigma_s \epsilon'_s \,;\ \epsilon'_s \underset{iid}{\sim} N(0,1) \tag{4.19}$$

A limitation of this specification is that it is silent on the feedback between sovereign risk and the economy's fundamentals.[43] On the other hand, this modeling strategy has the advantage that the sovereign risk process of equation (4.19), together with the reduced-form productivity loss of equation (4.3), are flexible enough to match the increase in Italian sovereign risk, as well as the increase in corporate risk caused by sovereign risk. As all the general equilibrium effects of the model operate through the bank-lending channel, matching these two paths is key for the analysis, given their direct implications on banks' balance sheets and on the supply of credit.

4.5 Pricing Kernels

In Appendix C.1, I show that the banks' stochastic discount factor (SDF) is given by:

$$\Xi\left(\boldsymbol{S'}, \boldsymbol{S}\right) \equiv \frac{\tilde{\beta}\Lambda(\boldsymbol{S'})}{\mu\left(\boldsymbol{S}\right)\kappa + \tilde{\beta} R_f \mathbb{E}\left(\Lambda(\boldsymbol{S'})\right)} \tag{4.20}$$

where $\Lambda\left(\boldsymbol{S'}\right) \equiv (1-\psi) + \psi\alpha\left(\boldsymbol{S'}\right)$. From equation (4.20), notice that the discount factor does not only depend on whether banks' leverage constraint is currently binding or not ($\mu\left(\boldsymbol{S}\right) \geq 0$), but it also depends on next-period's aggregate state $\boldsymbol{S'}$. News affecting sovereign and corporate risk, even when they do not lead to a binding leverage constraint,

[41]If the government is currently in default, the next-period default status is given by:

$$h'_G = \begin{cases} 0 & \text{if } \epsilon'_{exit} < \zeta \\ 1 & \text{otherwhise} \end{cases}$$

where ϵ'_{exit} is a uniform $[0,1]$ random variable.

[42]This is the same specification as in Bocola (2016). Under this setting, notice that government's next-period default probability is given by $1 - \frac{1}{1+exp(s)}$.

[43]For instance, an increase in sovereign risk may induce a decline in TFP, which further increases the government's default incentives. Arellano et al. (2019) provide a model that analyzes this type of feedback.

may still affect the bank's current SDF as they affect the likelihood that the constraint may bind in the future.

The pricing kernels for both the firms and the government are given by (see Appendix C.1 for the derivation):

$$q\left(k',b',z;\boldsymbol{S}\right) = \mathbb{E}\Bigg[\Xi\left(\boldsymbol{S'},\boldsymbol{S}\right)\Bigg(\left[1-h\left(k',b',z';\boldsymbol{S'}\right)\right]\times M_f(k',b',z';\boldsymbol{S'})+ \\ + h\left(k',b',z';\boldsymbol{S'}\right)\times R\left(k',b',z'\right)\Bigg)\Bigg] \tag{4.21}$$

and

$$q_B\left(\boldsymbol{S}\right) = \mathbb{E}\left[\Xi\left(\boldsymbol{S'},\boldsymbol{S}\right)\left(\left[1-h_G\left(\boldsymbol{S'}\right)\right]\times M_G(\boldsymbol{S'}) + h_G(\boldsymbol{S'})\times q_B(\boldsymbol{S'})\frac{B}{B'}\right)\right] \tag{4.22}$$

with $M_f(k',b',z';\boldsymbol{S'}) \equiv (1-m_f)\left(c_f + q\left(k'',b'',z';\boldsymbol{S'}\right)\right) + m_f$, and $k'' \equiv k'(k',b',z';\boldsymbol{S'})$ and $b'' \equiv b'(k',b',z';\boldsymbol{S'})$ denote the next-period firm's optimal policy functions. Also, $M_G(\boldsymbol{S'}) \equiv (1-m_G)\left(c_G + q_B\left(\boldsymbol{S'}\right)\right) + m_G$, and $B' = B'(\boldsymbol{S})$ denotes the government's current choice of debt.

4.6 Equilibrium

Let $\boldsymbol{S} = (s, B, N, h_G, \Omega)$ denote the aggregate state space, where s is the sovereign risk process, B is the government's stock of debt, N is the aggregate net worth of banks, h_G is the government's default status, and Ω is the distribution of firms across the three idiosyncratic states, (k, b, z). A recursive competitive equilibrium for this economy is: (i) a set of value functions for firms $\{V(k,b,z;\boldsymbol{S})\}$, households $\{W_h\left(x;\boldsymbol{S}\right)\}$, and bankers $\{W\left(\eta;\boldsymbol{S}\right)\}$; (ii) a set of policy functions for firms $\{b'(.,\boldsymbol{S}),\ k'(.,\boldsymbol{S}),\ h(.,\boldsymbol{S})\}$, households $\{c\left(.,\boldsymbol{S}\right),\ x'(.,\boldsymbol{S})\}$, and for bankers $\left\{\hat{b}(.,\boldsymbol{S}),\ \hat{B}(.,\boldsymbol{S}),\ \hat{x}(.,\boldsymbol{S})\right\}$; (iii) pricing functions $\{q\left(.,\boldsymbol{S}\right),\ q_B\left(\boldsymbol{S}\right)\}$; and (iv) a perceived law of motion for the aggregates $H\left(\boldsymbol{S}\right)$, such that:

1. Given prices and $H\left(\boldsymbol{S}\right)$, the firm's, bank's and household's policies solve their decision problems, and $\{V,\ W_h,\ W\}$ are the associated value functions.
2. The government's budget constraint is satisfied.
3. The markets for loans, government's bonds, deposits, and goods clear.
4. The law of motion $H\left(\boldsymbol{S}\right)$ for the aggregates is consistent with agents' optimization and the exogenous government's fiscal rules.

5 Quantitative Analysis

5.1 Numerical Solution

The model described in Section 4 features heterogeneity across firms, aggregate uncertainty, and important nonlinearities. At the firm-level, the nonlinearities arise from the firm's default choice, while at the aggregate level, they arise from the banks' occasionally binding leverage constraint. Due to the presence of these nonlinearities, I rely on global methods to solve the model. Moreover, the combination of firm heterogeneity and aggregate uncertainty implies that the distribution of firms (Ω), an infinite-dimensional object, is a state variable in the agents' decision problem. From equations (4.15) and (4.20), it is clear that the distribution of firms affects the demand for loans and therefore the banks' stochastic discount factor, implying that firms need to predict the evolution of this distribution to make their optimal choices regarding investment and debt issuance. I follow the bounded-rationality approach of Krusell and Smith (1998) to reduce the dimensionality, using a finite set of moments (R) that summarizes this distribution.

Even after summarizing the firm distribution with a finite set of moments, the model features 8 state variables: $\left(k, b, z, \tilde{S}\right)$, with $\tilde{\boldsymbol{S}} \equiv (s, B, N, h_G, R)$, and therefore it is subject to the curse of dimensionality. The algorithm used to solve the model relies on the use of graphics processing units (GPUs) to highly parallelize the solution. Modern GPUs have hundreds of cores (as opposed to 4-32 cores in today's CPUs) and are, therefore, a great alternative to solve problems that can be expressed as data-parallel computations (see for instance Aldrich et al., 2011). Appendix C.3 describes the algorithm.

5.2 Calibration

The calibration of the model is done in two steps. First, I calibrate the parameters relative to the firms' problem to match features of the Italian economy before the European debt crisis. This step is done for the model's non-stochastic steady state and under the assumption that the banks' leverage constraint does not bind. In the second step, I calibrate the parameters related to the government's and banks' problems for an economy that is subject to sovereign risk, taking as given the parameters calibrated in the first step. One period corresponds to one quarter. Table 5.1 summarizes the values for all the parameters of the model.

Parameters for the Firms' Problem. The parameters governing the production and investment technologies (α, χ, δ) are calibrated using values that are standard in the literature. The value-added share of capital in the Cobb-Douglas production function (α) is set to 0.3, the parameter governing the decreasing returns to scale (χ) is set to 0.85, and the quarterly depreciation rate (δ) is set equal to 0.025.[44] The corporate tax rate τ targets an effective corporate tax rate of 22%. The rest of parameters are calibrated to

[44]The calibration for these three parameters is the same as in Gilchrist et al. (2014).

match features of the panel of publicly traded Italian firms described in Section 2 for the 2003-2009 period. The parameters related to the idiosyncratic productivity process, ρ_z and σ_z, are calibrated to match the dispersion of the firm size distribution. In particular, they are set to match the ratios between the $25th - 50th$ and $50th - 75th$ percentiles for the firms' stock of capital (in logs).[45] The discount factor β targets the median profits-to-capital ratio, as it governs the firms' desire to accumulate capital. The purchase price of capital P_+ is normalized to one and P_- targets an average leverage ratio of 60%. While ψ captures the adjustment cost of investment, a small value of ψ leads to large swings in investment and also in leverage. As changes in firms' leverage have important implications on banks' net worth and therefore on the aggregate economy, I calibrate ψ to match the quarterly autocorrelation of leverage. The parameter m_f targets and average corporate loan maturity of 2.5 years, as reported by the Banca d'Italia.[46] I calibrate the coupon payments, c_f, in order to match the debt services for the panel of Italian firms.[47] Banca d'Italia reports an average recovery rate of corporate loans (for unsecured positions) of 23% for the 2006-2009 period. In the model, the recovery rate is affected by P_-, λ, and the adjustment costs. To simplify the analysis, I set $\lambda = 1$, which delivers an average recovery rate of 15%.[48] Finally, a_d and σ_d are calibrated to match the average default rate and spreads for Italian non-financial firms.[49]

Parameters for the Banks' and Government's Problems. With respect to the parameters governing the banks' problem, I set $\tilde{\beta} = 0.99$ targeting an annual risk-free rate of around 4%.[50] The banks' survival rate, ψ, is set to 0.96, which is the value estimated in Bocola (2016). The share of divertible assets, κ, is set to 0.23, as in Gertler et al. (2019). The parameter related to the transfers of the household to the entrant banker, γ, is internally calibrated to match the median leverage of the Italian banks in the ABI dataset.[51]

[45] The measure of capital includes gross property, plant, and equipment. It excludes reserves for depreciation, depletion, and amortization.

[46] This is the maturity for the entire universe of corporate loans in Italy. Banca d'Italia reports corporate loans across three maturity tranches (0-1, 1-3, and more than five). The average maturity is computed as the weighted average across tranches, using the lower bound of each tranche as the maturity. In this sense, the targeted moment represents a lower bound.

[47] Debt services are proxied with the share of short-term debt that matures within a year. In quarterly terms, this share represented 17% of the total debt during 2009. Given the calibrated value for m, I set $(m + (1 - m)c) = 0.17$ and solve for c. This is done purely due to data limitations. When calibrating debt services for government debt, the analysis also includes the interest payments on long-term debt.

[48] The recovery rate reported by the Banca d'Italia includes the interest payments paid by the borrower until the default. A better measure of the recovery rate, in the light of the model, is the price at which banks can sell their non-performing loans. For unsecured positions, this price averaged 10% of the book-value of the loan during 2016-2018. Unfortunately, no data prior to 2016 is publicly available.

[49] Default rates and spreads are based on the entire universe of non-financial Italian firms. Corporate spreads are computed as the difference between bank lending rates to non-financial corporations (as reported by the Bank of Italy) and the short-term Euro repo rate (reported by the ECB). The default rate is based on the number of defaulting non-financial firms (also from the Bank of Italy).

[50] As a reference, the discount rate on short-term Euro repo was 3.96% during 2007.

[51] To closely follow the measure of leverage implied by the model, using banks' balance-sheet data from the ABI dataset, I compute leverage as the ratio between sovereign bond holdings plus loans to

Table 5.1: Calibration

Parameter	Description	Value	Target/Source
α	Capital Share	0.30	Gilchrist et al. (2014)
χ	Dec. Returns to Scale	0.85	Gilchrist et al. (2014)
δ	Depreciation Rate	0.025	Gilchrist et al. (2014)
τ	Tax Rate	0.22	Effective Corporate Tax Rate
ρ_z	Persistence of TFP	0.95	Firm Distribution
σ_z	Volatility of TFP	0.09	Firm Distribution
β	Discount Factor	0.94	Profits-to-Capital
P_+	Purchase Price of Capital	1.00	-
P_-	Re-sell Price of Capital	0.50	Non-fin Leverage
ψ	Adj. Cost	1.00	Autocorrelation of Leverage
m_f	1/Loans Maturity	0.10	Loans Maturity
c_f	Coupon	0.08	Loans Services
λ	Recovery Rate	1.00	Recovery Rate (firms)
a_d	Exit Value (mean)	0.10	Default Rate & Spreads
σ_d	Exit Value (sd)	0.80	Default Rate & Spreads
$\tilde{\beta}$	Discount Factor	0.99	Risk-free rate
ψ	Survival Rate	0.96	Bocola (2016)
κ	Share Divertible Assets	0.23	Gertler et al. (2019)
γ	Transfer to Entrant Banker	0.45	Banks' Leverage
ρ_s	Sovereign Risk Process	0.99	Bocola (2016)
σ_s	Sovereign Risk Process	0.96	Bocola (2016)
$s^\star$	Sovereign Risk Process	-7.06	Bocola (2016)
m_G	1/Maturity	0.0375	Gov. Maturity
c_G	Coupon	0.037	Debt Services
f_B^1	Fiscal Rule	0.10	-
f_B^0	Fiscal Rule	-0.051	Banks' share of Gov. Bonds
$\underline{B}$	Default Haircut	0.35	Recovery Rate (gov)
ζ	Prob. Exit Default	0.10	Duration of Default
ξ_D	Aggregate Default Cost	0.85	Rigobon and Sack IV estimate

Notes: This table shows the calibration of the model. Top panel shows the parameters governing the firms' problem. Middle panel is for the banks' problem. Bottom panel refers to the parameters regarding the government's problem and the aggregate output losses if the government default.

With respect to the parameters behind the government's problem, the parameters governing the sovereign risk process (ρ_s, σ_s, and $s^\star$) are taken from Bocola (2016). The parameter m_G is calibrated to match an average maturity for Italian sovereign bonds of 80 months, as reported by the Italian Treasury Department. Also, c_G is set to match debt services of the Italian government.[52] Regarding the exogenous fiscal rule, f_B^1 is set at 0.1 and f_B^0 is internally calibrated to match the ratio of government's bond to non-financial loans in the balance sheet of Italian banks.[53] The parameter $\underline{B}$ targets an

non-financial firms relative to banks' net worth.

[52]Debt services includes both debt that matures within a year as well as interest payments. The Italian Treasury Department reports an average share of debt maturing within a year of 24.5%, for the 2003-2009 period. Moreover, as reported by the ECB, annual interest payments account for 4.5% of Italian sovereign debt outstanding. Given the calibrated value for m_G, I set $(m_G + (1 - m_G)c_G) = 0.29/4$ and solve for c_G.

[53]In the model, banks only have two assets: sovereign bonds and loans to non-financial firms. I calibrate f_B^0 to match a ratio of 22%, which is the median value observed in 2007 for the Italian banks in the ABI dataset. As transfers are lump-sum, different values of f_B^1 have small aggregate implications.

average recovery value of 50%, which is towards the upper end of the values used in the literature. The probability of exiting a sovereign default, ζ, targets an average duration of default of 2.5 years, in line with the range of values used in the literature.

Finally, the aggregate productivity loss in the event of a sovereign default, ξ_D, is internally calibrated to match the observed increase in corporate risk. Given that sovereign risk is exogenous in the model, I calibrate the parameter ξ_D to match the empirical estimates of Section 2. As those estimates are based on annual changes in the CDS of the Italian government, they need to be adjusted in order to make the connection with the quantitative model. Appendix A.9 converts the CDS spreads into quarterly risk-neutral default probabilities and then computes the Rigobon and Sack IV estimates as explained in Section 2. The estimates reported in Table A.17 imply that a 1pp increase in the quarterly risk-neutral default probability of the Italian government leads to a 0.13pp increase in quarterly corporate risk. The parameter ξ_D is set to match this estimate.[54]

5.3 Targeted and Untargeted Moments

In this section, I asses whether the model can accurately approximate the targeted moments as well as selected untargeted moments. I start with a description of moments for the non-stochastic steady state, in which government debt is not subject to sovereign risk and banks' stochastic discount factor is constant and equal to the (inverse of) risk-free rate. I then describe moments for the case with aggregate risk and occasionally binding leverage constraint. Finally, I feed the model with the observed path of Italian sovereign risk to evaluate how well it can explain the dynamics of the Italian sovereign debt crisis.

Non-Stochastic Steady State

Table 5.2 summarizes all the targeted steady state moments for the economy without aggregate risk. Overall, the model does a great job in approximating all the targets. First, the model replicates well the targeted percentiles of the firm distribution as well as the ratio of profits to capital for the panel of publicly traded firms described in Section 2. It also matches the two targeted moments with respect to non-financial leverage (mean and autocorrelation). With respect to the recovery rate, the model implies a recovery of 15% in terms of the book-value of the loan, which is in line with the recovery rates observed in Italy. Finally, it is also able to match the targeted non-financial default rates and loan spreads.

Figure 5.1 compares the model-implied distribution with the distribution of firms for the panel of publicly traded Italian corporations of Section 2.[55] The model does a good job

[54]The calibrated parameter is in line with previous studies that quantify the costs of sovereign defaults. For instance, based on Argentina's 2001 default, Sandleris and Wright (2014) estimate an aggregate productivity loss of 11.5%.

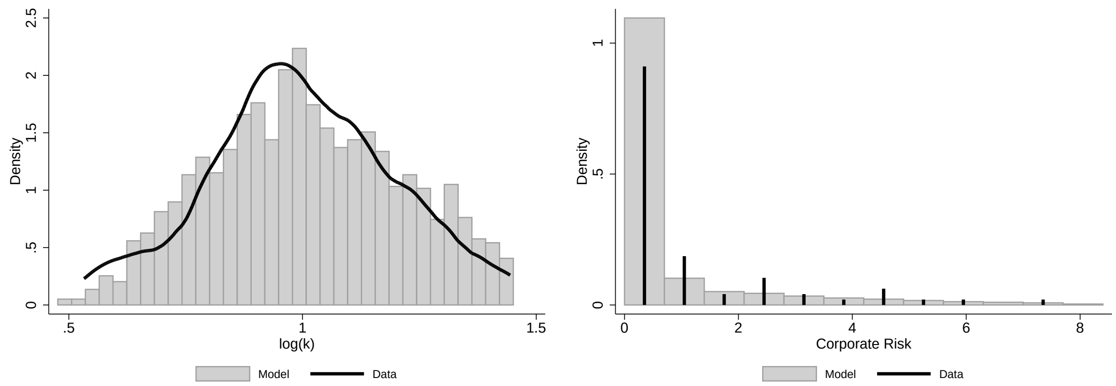
[55]Figures for the Italian data are based on 2009, the year before the spike in Italian sovereign risk. Results are similar when using the post-crisis period, 2015-2019.

Table 5.2: Non-Stochastic Steady State - Targeted Moments

Targeted Moments (Steady State)	Data	Model
$log(k)$: $25th/50th$ percentile	0.879	0.859
$log(k)$: $75th/50th$ percentile	1.136	1.158
Quarterly Profits-to-Capital	0.093	0.105
Leverage (mean)	61%	58%
Leverage (autocorr)	0.84	0.88
Recovery Rate (firms)	10-23%	15%
Firms' Default Rate	1.84%	1.94%
Firms' Spreads	2.27%	2.15%

Notes: The table shows the set of data moments targeted in the calibration and their model counterpart. The model-implied moments are based on $1,000$ quarters of simulated data for a sample of $2,000$ firms.

Figure 5.1: Non-Stochastic Steady State - Firms' Distribution



Notes: Figure compares the distribution implied by the model and the distribution for the panel of publicly traded Italian firms of Section 2. The left-hand-side panel depicts the distribution of firms by their stock of capital (in logs). The measure of capital includes gross property, plant, and equipment. It excludes reserves for depreciation, depletion, and amortization. The right-hand side depicts the distribution of firms by corporate risk. In the model, corporate risk is given by the default probability of the firm. In the data, it is given by the Merton distance to default computed in Section 2. The distributions for the Italian data are based on 2009.

Table 5.3: Economy with Sovereign Risk - Targeted and Untargeted Moments

Targeted Moments	Data	Model
Recovery Rate (gov)	50%	54%
Banks' Leverage	5.20	4.83
Banks' share of Gov. Bonds	21.7%	23.1%
$\frac{\Delta CR}{\Delta SR}$ (regression coefficient)	0.13	0.12
Untargeted Moments	**Data**	**Model**
$\sigma(GDP_t)$	1.45%	0.94%
$\sigma(Investment_t)$	5.27%	8.09%
$\sigma(BankLeverage_t)$	5.88%	7.35%
$\sigma\left(FirmDebt_t\right)$	3.31%	1.87%
$\sigma(CorpRisk_t)$	14.7%	9.31%
$\rho\left(SovRisk_{t-1}, GDP_t\right)$	-0.681	-0.697
$\rho\left(SovRisk_{t-1}, BankLeverage_t\right)$	0.475	0.322

Notes: The top panel shows the set of data moments targeted in the calibration and their model counterpart. The $\frac{\Delta CR}{\Delta SR}$ regression coefficient for the "Data" column corresponds to the Rigobon and Sack (2004) IV instrument, as described in Appendix A.9. The $\frac{\Delta CR}{\Delta SR}$ regression coefficient for the "Model" column corresponds to an OLS estimate, as implied by the model simulations. The bottom panel compares selected untargeted moments. Data moments are computed using quarterly data for the 2010-2012 period.

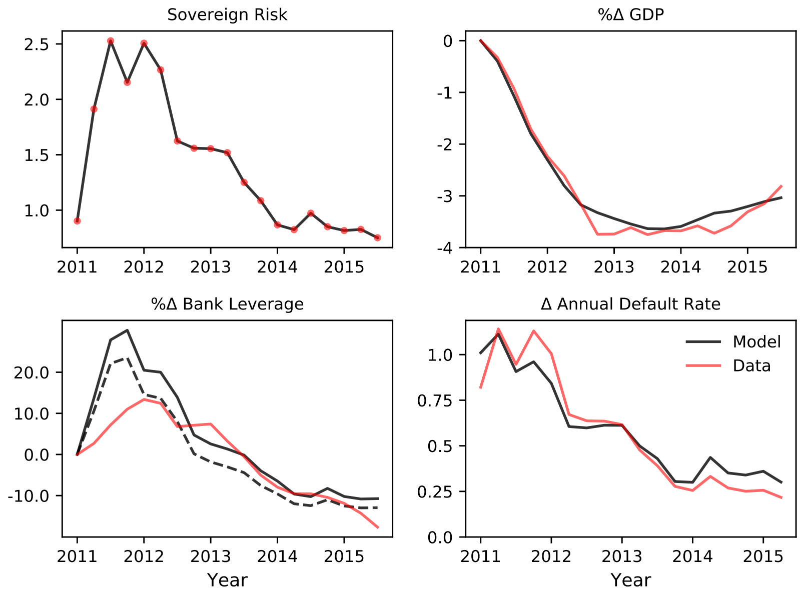
in matching the distribution of firms in terms of size (left panel) and, most importantly, in terms of risk (right panel). For the majority of the Italian firms in the sample, (pre-crisis) corporate risk is below 1% and the model is able to match this feature of the data. As already shown in Section 2, firms with higher pre-crisis levels of corporate risk are the ones most affected by the sovereign crisis. Matching the risk distribution observed in the data is, therefore, crucial to understand the role of these riskier firms in the transmission of sovereign risk, which is the analysis done in subsection 5.4.

Economy with Aggregate Risk

For the economy with aggregate uncertainty, the top panel of Table 5.3 shows that the model closely approximates the targeted moments for government's recovery rate, banks' leverage, and banks' share of government bonds. Most importantly, the model is able to match the Rigobon and Sack IV estimate for the relation between sovereign and corporate risk. The model-implied estimate is based on a simple OLS regression given that, in the model, sovereign risk is exogenous (there is no feedback between sovereign and corporate risk).[56] The bottom panel of Table 5.3 shows that the model can also approximate several untargeted moments. In particular, it replicates key moments of the Italian economy during the 2010-2012 period reasonably well. For instance, the volatilities of GDP, investment, banks' leverage, firms' debt, and corporate risk, as well as the correlations between sovereign risk, GDP, and banks' leverage.

[56]Put it differently, the model implied OLS and IV estimates are identical.

Figure 5.2: Model Implied Dynamics vs. Data



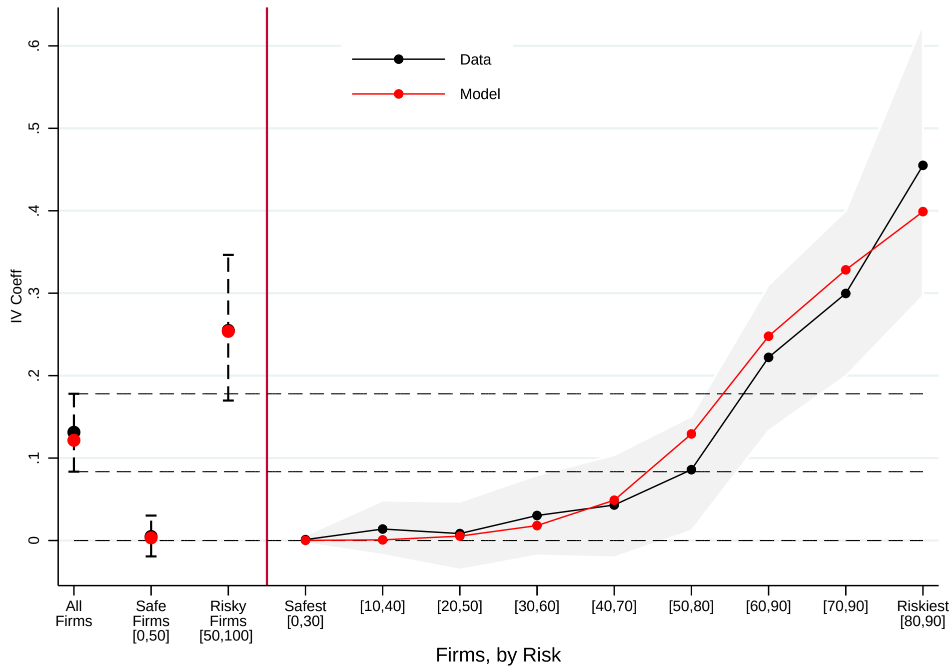
Notes: Figure compares the model-implied outcomes with Italian data. The model is fed with a sequence of sovereign shocks, $\{s_t\}$, that replicates the evolution of Italian quarterly default probability (computed from annual CDS, as explained in Appendix A.9). Red lines correspond to the Italian data. Black lines are based on the model simulations. Dashed lines in the leverage panel shows the model implied dynamics for a book-value measure of leverage. Sample period: 2011.Q2-2015.Q2. The change in the empirical default rate is given by the Rigobon and Sack IV estimate (described in Appendix A.9) times the change in sovereign risk (relative to a simulation with constant risk).

Figure 5.2 feeds the model a sequence of shocks to the $\{s_t\}$ process in order to replicate the observed path of Italian sovereign risk during the crisis and the recovery period.[57] Overall, the model does well in matching the evolution of three key variables: GDP, bank leverage, and non-financial default rate. The model does not only match the size of the recession, but also the persistence of the crisis.

A key message of the empirical analysis in Section 2 is that there are important heterogeneous effects across firms in the transmission of sovereign to corporate risk. In particular, as shown in Figure 2.4, firms with larger pre-crisis corporate risk are the ones most affected by the sovereign shock. Figure 5.3 shows that the quantitative model is able to reproduce this heterogeneous transmission. As shown in subsection 5.5, this heterogeneous response can be exploited to construct policies that effectively dampen the negative effects of an increase in sovereign risk.

[57] The analysis starts in the second quarter of 2011, period in which Italian CDS increased sharply, as shown in Figure 2.1.

Figure 5.3: IV Coefficients, by Firms with Different Risk - Model vs Data



Notes: Figure compares the Rigobon and Sack IV estimates based on Italian data with the model implied OLS estimates. The x-axis sorts firms according to their pre-crisis risk profile. Red lines show the model implied OLS coefficients. Black lines show the IV estimates for the Italian data, which are computed as described in Appendix A.9. Sample period is April 2010 - April 2012. Grey area depicts the 90 percent confidence intervals, based on a percentile stratified bootstrap.

5.4 Decomposing the Effects & Role of Firm Heterogeneity

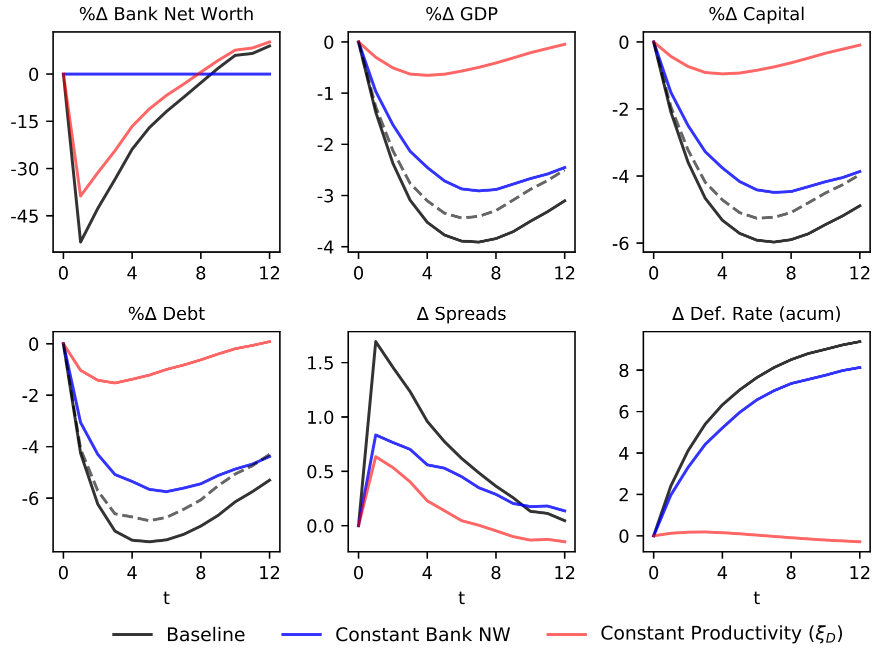
In this section, I present counterfactuals to understand how corporate risk can amplify the macroeconomic effects of an increase in sovereign risk, and to highlight the role of firms' heterogeneity behind this amplification mechanism.

I start by decomposing the effects in two channels: the (endogenous) bank-lending channel and the exogenous variation in corporate risk, captured by the productivity loss ξ_D that occurs in the event of a sovereign default. Figure 5.4 presents the impulse response of six key variables to a three standard deviation increase in sovereign risk.[58] For the baseline economy (solid black lines), an increase in sovereign risk induces a sharp decrease in banks' net worth. It also leads to higher spreads and default rates for non-financial firms, as well as a lower production, investment, and firms' stock of debt. The blue solid lines depict a counterfactual in which the bank-lending channel is shut down by keeping banks' net worth constant.[59] In this case, banks' balance sheets are unaffected

[58] The shock last for about 12 quarters. In all the simulations, the government never defaults.

[59] This is done in an MIT shock way. That is, when running the model's simulation, at the begging of each period and irrespectively of the "true" evolution of banks' net worth, I set a $NW_t = NW_{t-1}$.

Figure 5.4: Decomposition of the Effects



Notes: Impulse response to a three standard deviation increase in sovereign risk. Figure compares the model-implied outcomes (black solid lines) with two different counterfactuals. Solid blue lines correspond to a counterfactual without the bank-lending channel, in which banks' net worth remains constant. Solid red lines show the results when the exogenous component of corporate risk is shut down ($\xi_D = 1.0$). Black dashed lines show the vertical sum of the two counterfactuals. In all the simulations, the government never defaults. Spreads are annualized and they are computed for the median firm. The last panel shows the cumulative change in the annualized default rate.

by changes in sovereign and corporate risk. By comparing with the baseline model, the figure shows that more than 40% of the decline in GDP and capital can be explained by the bank-lending channel, highlighting the importance of this mechanism. The bottom-right panel shows that the increase in the default rate of non-financial firms is dampened under this counterfactual, consistent with the empirical results described in Section 3. Lastly, the increase in banks' spreads is also dampened. Under this counterfactual, banks increase their spreads only due to the larger credit risk of firms and not because they are constrained in their capacity to provide credit.

The red solid lines of Figure 5.4 show the dynamics for a counterfactual in which firms' productivity is unaffected by a sovereign default ($\xi_D = 1$). This case can be interpreted as an economy in which corporate risk is not influenced by sovereign risk, apart from the effects that operate through the bank-lending channel. The figure shows that corporate risk plays a crucial role in explaining the size and persistence of the crisis. Once corporate risk is shut down, the drop in aggregate output is significantly dampened and the economy recovers faster.[60] Moreover, relative to the baseline economy, banks' net worth decreases

[60]This result is in line with the results in Bocola (2016). For a 3.5 standard deviation increase in

almost a third less upon impact, which highlights the important role of corporate risk on banks' balance sheets.

Having decomposed the individual effects, I next explore the amplification mechanism between sovereign and corporate risk that operates through the bank-lending channel. The dashed black lines in Figure 5.4 (for the GDP, capital, and debt panels only) show the dynamics when adding up the individual impulse responses of the previous counterfactuals (i.e., the vertical sum of the red and blue lines). Unlike the baseline model, this counterfactual ignores the feedback loop between corporate risk and banks' net worth. By further weakening banks' net worth, this mechanism amplifies the size of the recession, as aggregate output decreases an additional 15% at the peak of the crisis. The feedback loop also slows the speed of the recovery, as firms delay their investments due to the smaller supply of credit.

Altogether, the previous decomposition highlights that non-financial risk plays a crucial role in the recession. I show that the contraction in the supply of credit by itself (i.e., ignoring the increase in corporate risk) only explains a relatively small fraction of the drop in aggregate output. Once corporate risk is introduced, the model is able to generate a much larger drop in aggregate output. While part of this drop is explained by the (exogenous) expectation of lower productivity upon a sovereign default, I show that the bank-lending channel plays an important role as it accounts for almost 40% of the decline in output. Lastly, I show that corporate risk has a sizable impact on banks' net worth. By further weakening banks' balance sheets, I find that the feedback between corporate risk and banks' net worth slows the speed of the recovery and increases the drop in aggregate output.

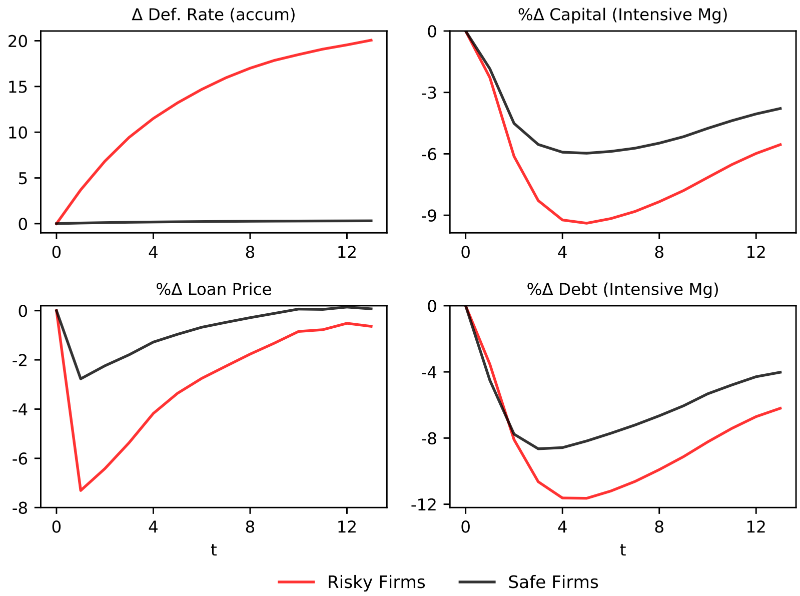
What is the role of firm heterogeneity behind the previous results? Figure 5.5 plots the same impulse response for firms with low and high levels of corporate risk (before the shock). In line with the results presented in Figure 5.3, the sovereign shock leads to a sharp increase in default rates of high-risk firms but it does not change the default frequency of safe firms. This different response leads to significant differences in the valuation of firms' debt. For risky firms, the value of their loans decreases four times more, relative to safe firms. The sharp decrease in banks' net worth shown in Figure 5.4 is, therefore, mainly driven by high-risk firms (and, obviously, by the increase in sovereign risk).[61] The right-hand side panels show that high-risk firms reduce their stock of capital and debt significantly more, as they face higher spreads due to the additional increase in their risk.

To sum up, the analysis shows that riskier firms reduce their investment more and are also behind the decrease in banks' net worth. Through their effects on banks' balance sheets, riskier firms, therefore, indirectly affect safer firms, amplifying the effects of the crisis. In the next section, I exploit this heterogeneity in firms' responses to provide policies that can better mitigate the negative effects of an increase in sovereign risk.

sovereign risk, Figure 5 in Bocola's paper shows a 0.30% decrease in output.

[61]The change in loan prices serves as a measure for the change in banks' net worth that is driven by changes in corporate risk.

Figure 5.5: Heterogeneous Dynamics



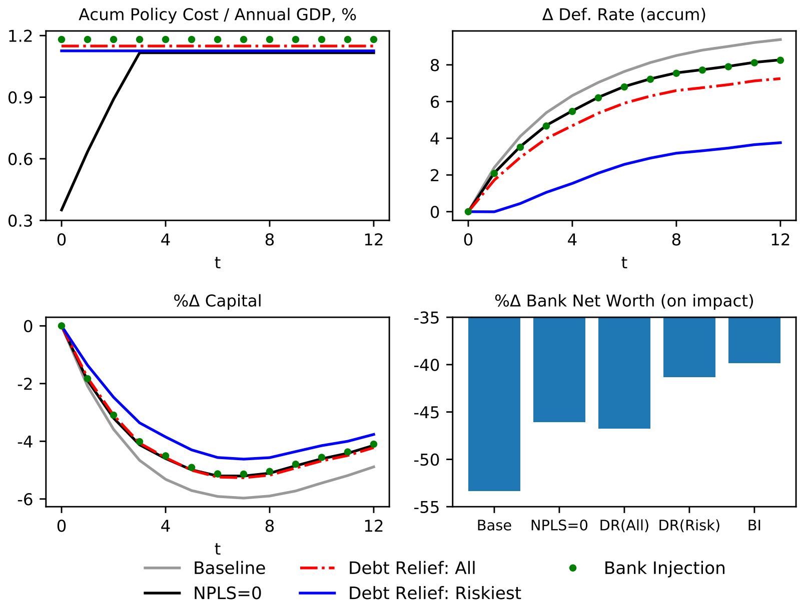
Notes: Impulse response to a three standard deviation increase in sovereign risk across firms with different (pre-shock) values of corporate risk. Red lines show the results for the "risky firms", i.e., those that are above the 50th percentile in terms of corporate risk before the shock. Black lines show the results for "safe firms", which are those below the 50th percentile. In all the simulations, the government never defaults. The top-left panel shows the cumulative change in the annualized default rate. Changes in capital and debt are for the intensive margin only as they exclude the effects of new entrants.

5.5 Breaking the Amplification Mechanism

In this section, I discuss different policies that can mitigate the negative effects of an increase in sovereign risk. Two types of policies are considered. First, I focus on policies that are homogeneous across all firms. Second, I provide an example of a policy that exploits firms' heterogeneous reaction to sovereign risk. For simplicity, I assume that these policies are financed with lump-sump taxes to households and they are all unexpected.

I start by considering policies that do not exploit firm heterogeneity. The first intervention is a government guarantee scheme. In this case, the government guarantees all the non-performing loans (NPLs) for four quarters since the time of the sovereign shock. While this policy does not directly affect the default incentives of the firms, it allows to ameliorate the decrease in banks' net worth, since the government pays back all the defaulted loans. The second intervention is a policy that directly injects capital into banks. For this policy, I assume that, at the time of the sovereign shock, the government makes a one-time capital injection in the banks, equivalent to $x\%$ of the banks' net worth. I choose x so that the cost of this policy is exactly the same as the cost of the government guarantee scheme. The third intervention is a homogeneous debt relief program across all firms. In this case, at the time of the shock, the government reduces the value of firms' debt by $y\%$, where y is chosen to match the costs of the previous policies.

Figure 5.6: Effects of the Policies

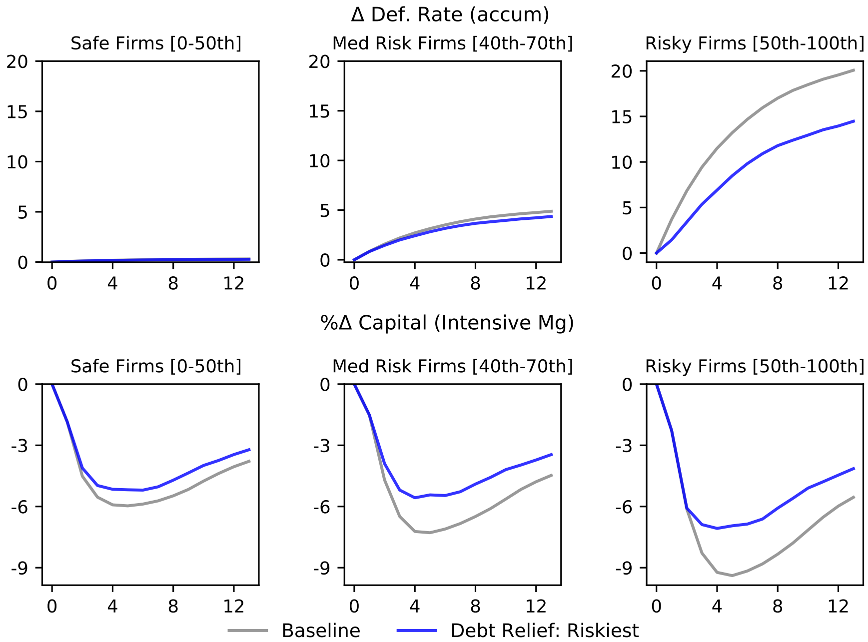


Notes: Impulse response to a three standard deviation increase in sovereign risk. Figure compares the model-implied outcomes (gray solid lines) with four different policies. Black solid lines correspond to the policy in which the government repays all the NPLs during the first four quarters after the sovereign shock. Green dots shows the results for an equity injection to banks. Red dashed lines show the dynamics for the case in which the government runs a homogeneous debt relief program across all firms. Blue solid lines show the dynamics for debt relief program targeted to the riskiest firms. In all the simulations, the government never defaults. The top-left panel shows the cumulative cost of each policy. The top-right panel shows the cumulative change in the annualized default rate. The bottom-right panel shows the change in banks' net worth on impact (at the time of the shock).

Next, I consider a policy intervention that takes into consideration firms' heterogeneous reaction to sovereign risk. As shown in Figure 5.5, only the riskier firms experience an increase in their corporate risk. This policy is targeted towards a subset of these firms. In particular, I assume that, at the time of the sovereign shock, the government reduces the debt of the riskiest firms by $z\%$ and I choose z so that the fiscal cost is the same as in the previous two policies. For illustration purposes, I define the "riskiest firms" as those with an annual default probability larger than 3%. This cutoff includes the firms above the $85th$ percentile in terms of the (pre-shock) firms' risk distribution.

Figure 5.6 depicts the dynamics for firms' default rate and capital, the accumulated costs of the policies, and the change in banks' net worth (on impact) for a three standard deviation increase in sovereign risk. The government guarantee scheme (black lines), the capital injection to banks (green dots), and the homogeneous debt relief program (red dashed lines) do not have a large impact on firms' default rates and they lead to almost identical dynamics for the economy's stock of capital. In contrast, the debt relief geared toward the riskiest firms (blue solid lines) leads to a sharp decline in firms' default rates and further reduces the decline in the aggregate stock of capital (and also in GDP) by

Figure 5.7: Heterogeneous Debt Relief Policy - Effects by Firms' Risk



Notes: Impulse response to a three standard deviation increase in sovereign risk. Figure compares the model-implied outcomes with a debt relief program geared toward the riskiest firms. Gray solid lines show the dynamics for the baseline model. Blue solid lines show the dynamics for the debt relief program targeted to the riskiest firms (those above the 85th percentile). In all the simulations, the government never defaults. Safe (risky) firms are those below (above) the 50th pctl. in terms of corporate risk before the shock. The middle panel shows the results for "medium" risk firms (those between the 40th and 70th pctls). The top panels show the cumulative change in the annualized default rate. Changes in capital are for the intensive margin only as they exclude the effects of new entrants.

almost 50% (relative to the other three policies). The underlying reason is that this policy achieves two goals at the same time: it avoids the default of the riskiest firms and it attains a lower contraction in banks' net worth. The smaller decline in banks' net worth is explained by the lower default rate and by the smaller drop in the valuation of firms' loans due to the overall reduction in corporate risk.[62] Notice that, the drop in banks' net worth attained by this policy is comparable to the policy that directly injects capital into banks.[63]

Figure 5.7 provides a decomposition of the effects of the heterogeneous debt relief policy by showing the dynamics for firms with different levels of risk. This figure highlights

[62]While the homogeneous debt relief program also affect the firms' loan value (as it affects firms' default incentives), a large share of the relief is designated towards safe firms, which, before and after the shock, have small default probabilities. Thus, on average, this policy does not have a sizable impact on loan values and banks' net worth.

[63]For the government guarantee scheme, the decline in banks' net worth depicted in Figure 5.6 underestimates the results given that this policy benefits banks for four quarters. After one year, the contraction in banks' net worth under this policy is similar to the decline observed under the capital injection policy.

important spillover effects that end up benefiting safer firms that are not directly targeted by the policy. By directly targeting those firms that are close to default, this policy leads to a lower decrease in banks' net worth, which in turn benefits safer firms as these can have access to cheaper credit. To sum up, this policy not only leads to a decrease in the default rate of the riskiest firms but also allows to ameliorate the amplification mechanism of sovereign and corporate risk that operates through the bank-lending channel.

6 Conclusion

I have presented a framework to study the role of corporate risk as an amplification mechanism for the macroeconomic effects of sovereign risk. In the empirical section, I used a heteroskedasticity-based approach to show that increases in sovereign risk cause a significant increase in non-financial default risk, and described important asymmetric effects across firms behind this transmission. Firms with higher (pre-crisis) default risk are significantly more affected by increases in sovereign risk. I then used bank-level data to show that the bank-lending channel is an important driver behind this transmission. Banks with higher sovereign exposures exhibit a larger increase in their corporate non-performing loans. Altogether, these results indicate that corporate risk amplifies the effects of sovereign risk by further weakening banks' balance sheets and that riskier firms play a crucial role in that amplification.

I formulated a heterogeneous-firms model in which non-financial risk is endogenously linked to sovereign risk through the banking sector, and I used the empirical estimates to discipline this relation. The model features a two-way feedback loop. On the one hand, the increase in sovereign risk decreases banks' net worth, leading to a lower credit supply and higher interest rates, which in turn increases the default risk of non-financial firms. On the other hand, as corporate risk increases, banks' net worth decreases even further, generating an amplification mechanism not studied before. By further weakening banks' balance sheets, I showed that this feedback mechanism significantly amplifies the size and persistence of the recession. I studied different policies that can mitigate the negative effects of an increase in sovereign risk and identified efficiency gains from policies that exploit firms' heterogeneous reactions to increases in sovereign risk.

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A The Transmission of Sovereign to Corporate Risk: Additional Material

A.1 List of Events

This appendix describes the set of foreign news events. Two types of events are considered: credit-rating downgrades and news about bailouts for Greece and Portugal. Tables A.1 and A.2 summarize the credit rating changes. The list includes rating and outlook changes from three main credit rating agencies: Fitch, Moody's, and Standard & Poor's, between April 2010 and April 2012. News about bailouts include the dates in which the ECB or IMF announced the different bailouts as well as the dates in which the bailout was approved. Table A.3 summarizes these events. The list includes news about the first and second Greek bailouts (2010 and 2012) as well as news about the Portuguese bailout in 2011. The set of events, moreover, includes the austerity packages approved by the Greek and Portuguese governments because these were requirements of the associated bailout programs.

Table A.1: List of Events - Credit Rating of Greece - Announcements

Agency	Rating	Outlook	Date of Announcement
Fitch	BBB-	negative	Apr 9, 2010
Fitch	BBB-	negative watch	Dec 21, 2010
Fitch	BB+	negative	Jan 14, 2011
Fitch	B+	negative watch	May 20, 2011
Fitch	CCC	n/a	Jul 13, 2011
Fitch	C	n/a	Feb 22, 2012
Fitch	RD	n/a	Mar 9, 2012
Fitch	B-	stable	Mar 13, 2012
Moody's	A3	negative	Apr 22, 2010
Moody's	Ba1	stable	Jun 14, 2010
Moody's	Ba1	negative watch	Dec 16, 2010
Moody's	B1	negative	Mar 7, 2011
Moody's	B1	negative watch	May 9, 2011
Moody's	Caa1	negative	Jun 1, 2011
Moody's	Ca	negative	Jul 25, 2011
Moody's	C	negative	Mar 2, 2012
S&P	BB+	negative	Apr 27, 2010
S&P	BB+	negative watch	Dec 2, 2010
S&P	BB-	negative watch	Mar 29, 2011
S&P	B	negative watch	May 9, 2011
S&P	CCC	negative	Jun 13, 2011
S&P	CC	negative	Jul 27, 2011
S&P	SD	n/a	Feb 27, 2012

Table A.2: List of Events - Credit Rating of Portugal - Announcements

Agency	Rating	Outlook	Date of Announcement
Fitch	A+	negative	Dec 23, 2010
Fitch	A-	negative watch	Mar 24, 2011
Fitch	BBB-	negative watch	Apr 1, 2011
Fitch	BB+	positive	Nov 21, 2011
Fitch	BB+	negative	Nov 24, 2011
Moody	Aa2	negative watch	May 5, 2010
Moody	A1	stable	Jul 13, 2010
Moody	A1	negative watch	Dec 21, 2010
Moody	A3	negative	Mar 15, 2011
Moody	Baa1	negative watch	Apr 5, 2011
Moody	Ba2	negative	Jul 5, 2011
Moody	Ba3	negative	Feb 13, 2012
S&P	A-	negative	Apr 27, 2010
S&P	A-	negative watch	Nov 30, 2010
S&P	BBB	negative watch	Mar 24, 2011
S&P	BBB-	negative	Mar 29, 2011
S&P	BBB-	negative watch	Dec 5, 2011
S&P	BB	negative	Jan 13, 2012

Table A.3: List of Events - News about Bailouts

Country	News date	Description
Greece	Apr 11, 2010	EMU and IMF agree on bailout plan for Greece.
Greece	May 2, 2010	Greek bailout is approved (110 billion euro).
Greece	May 6, 2010	Greek parliament passes austerity measures to meet EMU's requirements for bailout.
Portugal	May 3, 2011	EMU and IMF agree on bailout plan for Portugal.
Portugal	May 17, 2011	Portugal bailout is approved (78 billion euro).
Portugal	Oct 13, 2011	Portugal approves austerity package.
Greece	Jun 8, 2011	Greece agrees another austerity package.
Greece	Jul 8, 2011	IMF approves bailout package (3.2 billion euros).
Greece	Jul 21, 2011	EMU and IMF agree on second bailout to Greece.
Greece	Oct 21, 2011	Greece approves more austerity measures to meet bailout requirements.
Greece	Dec 7, 2011	New Greek coalition passes another austerity package.
Greece	Feb 12, 2012	Greek parliament endorses another austerity deal.
Greece	Feb 21, 2012	Greek second bailout is approved (130 billion euro).

The list of events described in the main text (and summarized in Table 2.1) includes all the bailout news in Table A.3. Given that credit rating changes from one agency are usually followed by announcements made by another agency, the main set of events excludes the announcements made within two weeks after a previous announcement.

For example, the Moody's announcement on April 22, 2010 and the Standard & Poor's announcement on April 27, 2010 are not included in the main set of events as they are within the 2-week period after the Fitch announcement on April 9, 2010.

In Appendix A.7, I show that the results are robust to different subsets of events. For instance, the estimates are in line with the ones described in the main text if the announcements of only one credit risk agency (either Fitch, Moody's, or Standard & Poor's) are included as events, when only news about Greek bailouts are included as events, and when the austerity packages news or the credit-rating downgrades are excluded. The analysis, therefore, shows that the main estimates are not driven by a particular subset of events. This is key in the context of the study. The period under analysis was characterized by a large volatility across Europe and several governments (including the Italian government) implemented different policies (for instance, large austerity packages) that may bias the results if the announcement of those policies coincide with the set of foreign news events. For completeness, Table A.4 shows a list of events in which the Italian credit rating was downgraded or in which the Italian government implemented austerity packages. In Appendix A.7, I show that the results are also robust to the exclusion of these events.[64]

Table A.4: List of Events - Italian News Events

Agency	Rating	Outlook	Date of Announcement
Fitch	A+	negative	Oct 7, 2011
Fitch	A+	negative watch	Dec 16, 2011
Fitch	A-	negative	Jan 27, 2012
Moody's	Aa2	negative watch	Jun 17, 2011
Moody's	A2	negative	Oct 4, 2011
Moody's	A3	negative	Feb 13, 2012
S&P	A+	negative	May 20, 2011
S&P	A	negative	Sep 19, 2011
S&P	A	negative watch	Dec 5, 2011
S&P	BBB+	negative	Jan 13, 2012

News date	Description
May 25, 2010	Italy approves a 24 billion euro austerity package.
Aug 12, 2011	Italy agrees 65 billion austerity package.
Sep 14, 2011	Italian parliament gives final approval to austerity plan.
Nov 11-13, 2011	Prime minister resigns. Additional austerity measures are approved.
Dec 3, 2011	Italy new prime minister passes new austerity package.

[64] In the main analysis, the week from 11/7/2011 - 11/13/2011 is excluded from the analysis as in this week the Italian Prime Minister, Silvio Berlusconi, resigned and, at the same time, the Italian government approved important austerity measures. Results are robust to the inclusion of these days.

A.2 Financial and Trade Links between Italy and Greece and Portugal

Using the European Banking Authority (EBA) 2011 Stress Test dataset, Table A.5 shows the sovereign exposure for five of the largest Italian banks to other European countries. In particular, their exposure to Greece and Portugal represents less than 0.7% of their entire sovereign exposure (which implies less than 0.1% of their assets). In fact, Italian banks were not significantly exposed to any of the other GIIPS countries and their total exposure to EEA countries (ex-Italy) accounts only for 12% of their total sovereign holdings. Table A.6 shows that Greek and Portuguese banks were not significantly lending to Italian firms. Lastly, Table A.7 shows that trade links between Italy and Greece and Portugal are also weak. Italian exports to these two countries represent less than 3% of its total exports (and only 0.6% of Italy's GDP). Italian imports from Greece and Portugal, represent around 1% of its total imports.

Table A.5: Sovereign Exposure by Country - Italian Banks

	Intesa	UNI	BPS	BP	UBI	Average
Italy	81.7	53.3	96.2	95.2	97.4	84.78
Spain	1.10	2.11	0.84	1.61	0.00	1.13
Greece	0.84	0.73	0.02	0.70	0.23	0.51
Portugal	0.10	0.10	0.60	0.00	0.00	0.16
Ireland	0.15	0.06	0.00	0.00	0.00	0.04
GIIPS-Ex Italy	2.20	3.00	1.46	2.31	0.23	1.84
EEA-Ex Italy	9.96	39.44	3.36	4.70	2.60	12.01

Notes: Table reports the sovereign exposure by country for five Italian banks, as a share of the total sovereign exposure. Intesa = Intesa Sanpaolo SpA; UNI = Unicredit; BPS = Banca Monte Dei Paschi di Siena SpA; BP = Banco Popolare; UBI BANCA = Unione Di Banche Italiane SCPA. EEA refers to the European Economic Area countries. GIIPS countries include Greece, Ireland, Italy, Portugal, and Spain. Results expressed as a fraction of the total sovereign exposure. Results expressed in percentages. Source: European Banking Authority 2011 Stress Test.

Table A.6: Exposures by Country

	Banks' Domicile					
Counterparty	Italy	Greece	Portugal	Germany	France	UK
Italy	66.55	0.10	0.48	2.74	6.35	0.82
Greece	0.05	71.42	2.02	0.47	1.07	0.18
Portugal	0.08	0.03	71.06	0.49	0.37	0.32
Germany	8.44	1.09	0.62	50.60	2.45	3.26
France	1.57	0.35	3.01	3.03	49.82	3.37
UK	1.03	2.05	2.49	5.71	4.30	44.13

Notes: Table reports the "Exposure at Default" (EAD) measure, as reported by the European Banking Authority. This measure includes (i) non-defaulted exposures and (ii) defaulted exposures. It includes exposures to: financial institutions, corporate firms (excluding commercial real estate), retail (excluding commercial real estate), and commercial real estate. It also includes securitization transactions, counterparty credit risk, sovereigns, guarantees by sovereigns, public sector entities, and central banks. Results expressed as a fraction of the total EAD by banks' domicile. Results expressed in percentages. Source: European Banking Authority 2011 Stress Test.

Table A.7: Trade Links by Country

	Italy's Share of Exports and Imports			
	$\frac{\text{Exports}}{\text{Total Exports}}$	$\frac{\text{Exports}}{\text{GDP}}$	$\frac{\text{Imports}}{\text{Total Imports}}$	$\frac{\text{Imports}}{GDP}$
Greece	2.04	0.44	0.69	0.15
Portugal	0.92	0.20	0.46	0.10
GIIPS (ex ITA)	9.53	2.05	8.19	1.82
World	100	21.46	100	22.17

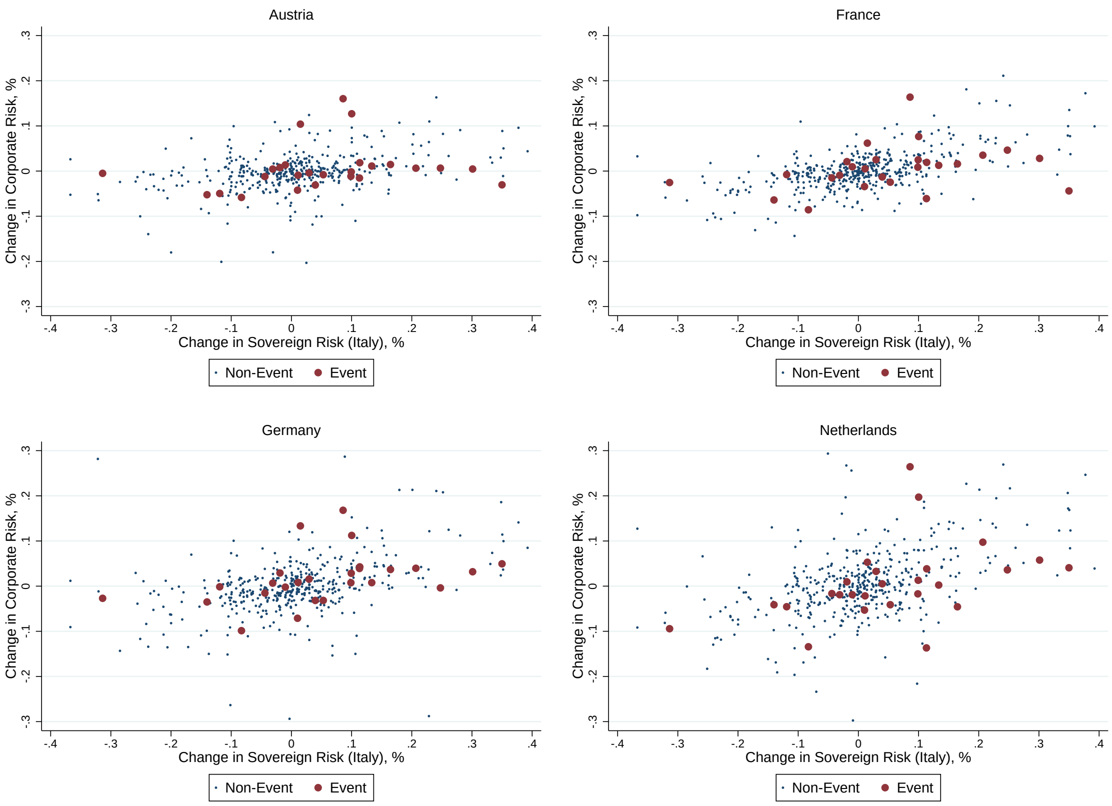
Notes: Table reports Italy's share of exports and imports, by country. Figures correspond to the 2009 year. Results expressed in percentages. The GIIPS (ex ITA) row includes exports (imports) to (from) Greece, Portugal, Spain, and Ireland. Source: OECD.

A.3 Summary of Events for Other European Countries

This section analyzes changes in corporate risk during event days for four other European countries: Austria, France, Germany, and the Netherlands. For each country, I construct a measure of corporate risk based on the Merton (1974) distance-to-default framework, following the same steps as the ones described in subsection 2.1. The firms included in the analysis are the constituents of the *DS non-financial Index* of each country.

Figure A.1 plots the daily change in the 10-year Italian government CDS versus the daily change in corporate risk for each country. Smaller dots represent non-event days while the larger red dots are for the foreign news event days. For non-event days, Italian sovereign risk co-moves with corporate risk across Europe. However, unlike the Italian case, there is no clear (positive) correlation between the Italian sovereign risk and each country's corporate risk during the event days. The results suggest that omitted common factors may not be important during the event days. A more formal analysis of common factors is presented in subsection 2.6.

Figure A.1: Corporate Risk across Europe vs Italian CDS



Notes: The figure plots the one-day change in the 10-year Italian government CDS and the average daily change in non-financial default risk for four European countries. Corporate risk is based on the Merton distance-to-default framework. Results report the unweighted average across all the firms in the sample. Sample period: April 2010 - April 2012.

A.4 Derivation of the Rigobon and Sack Instrument

This section follows Rigobon and Sack (2004) to explain how the main estimator of subsection 2.4 is constructed.

First, we can rewrite the system of equations in (2.5)-(2.6) as the following reduced form:

$$\Delta CR_t = \left(\frac{1}{1-\alpha_1\beta_1}\right)(\alpha_0 + \alpha_1\beta_0 + [\alpha_2 + \alpha_1\beta_2]\, X_t + \alpha_1\eta_t + \epsilon_t)$$
$$\Delta SR_t = \left(\frac{1}{1-\alpha_1\beta_1}\right)(\beta_0 + \beta_1\alpha_0 + [\beta_2 + \beta_1\alpha_2]\, X_t + \beta_1\epsilon_t + \eta_t)$$

Using the last two expressions, it is easy to write the variance-covariance matrix as:

$$\Gamma_j = \left(\frac{1}{1-\alpha_1\beta_1}\right)^2 \begin{bmatrix} (\alpha_2+\alpha_1\beta_2)^2\,\sigma^2_{F,j} + \alpha_1^2\sigma^2_{\eta,j} + \sigma^2_{\epsilon,j} & [\alpha_2+\alpha_1\beta_2]\,[\beta_2+\beta_1\alpha_2]\,\sigma^2_{F,j} + \alpha_1\sigma^2_{\eta,j} + \beta_1\sigma^2_{\epsilon,j} \\ . & (\beta_2+\beta_1\alpha_2)^2\,\sigma^2_{F,j} + \beta_1^2\sigma_{\epsilon,j} + \sigma^2_{\eta,j} \end{bmatrix}$$

for each set of events $j = \{E, N\}$. Under the assumption that $\sigma_{F,E} = \sigma_{F,N}$ and $\sigma_{\epsilon,E} = \sigma_{\epsilon,E}$, the difference in the variance-covariance matrix between event and non-event days can therefore be expressed as:

$$\Delta\Gamma = \lambda \begin{bmatrix} \alpha_1^2 & \alpha_1 \\ \alpha_1^2 & 1 \end{bmatrix}$$

where $\lambda \equiv \left(\frac{1}{1-\alpha_1\beta_1}\right)^2 \left[\sigma^2_{\eta,E} - \sigma^2_{\eta,N}\right]$.

A.5 Test of Differences in Variances

I present here an F-test to verify the main assumption of the Rigobon and Sack approach, namely that the variance of the shocks to the changes in sovereign risk is larger during the event days. As it can be viewed from the previous expression, the Rigobon and Sack instrument is relevant only under the assumption that $\lambda > 0$. To test this, I conduct a hypothesis test that $\sigma(\Delta SR)_E = \sigma(\Delta SR)_N$, using Levene (1960) and Brown and Forsythe (1974) methods. Table A.8 reports the results. Both tests strongly reject the hypothesis of equal variances, providing evidence in favor of $\lambda > 0$. The table also reports the results for the test $\sigma(\%\Delta SR)_E = \sigma(\%\Delta SR)_N$, given that, in some of the robustness exercises, the percentage change in sovereign risk is used as a regressor.

Table A.8: Test of Differences in Variance

Variable	$\sigma_j(\Delta SR_t)$		$\sigma_j(\%\Delta SR_t)$	
Value	**Event**	**Non-Event**	**Event**	**Non-Event**
	0.1837	0.1297	7.367	4.411
Test	**F-statistic**	**p-value**	**F-statistic**	**p-value**
Levene's	7.3051	0.0071	13.0167	0.0003
B&F, median	7.2209	0.0075	13.0459	0.0003
B&F, trimmed mean	7.2263	0.0074	13.0648	0.0003
Observations	493			

Notes: The table reports Levene's (1960) robust test statistic for the equality of variances of changes in Italian sovereign risk between the event and non-event days. It also displays the two statistics proposed by Brown and Forsythe (1974) that replace the mean in Levene's formula with alternative location estimators. These reformulations are more robust than Levene's test when dealing with skewed populations. The "B&F median" replaces the mean with the median. The "B&F trimmed mean" replaces the mean with the 10% trimmed mean.

A.6 Model with More than One Group

This section shows how the Rigobon and Sack (2004) method can be easily extended to two or more groups of firms. Instead of being the country's average corporate risk, assume now that ΔCR_t is a vector, formed by the default risk of N groups of non-financial firms. That is:

$$\Delta\left[CR_t\right] = \begin{bmatrix} \Delta CR_{1,t} \\ \dots \\ \Delta CR_{i,t} \\ \dots \\ \Delta CR_{N,t} \end{bmatrix}$$

In the main text, I think of i's as quantiles of the (pre-crisis) distribution of firms' corporate risk. Consider now the following model, in which (for simplicity) there are no spillovers across groups of firms:

$$\begin{aligned} \Delta\left[CR_t\right] &= \alpha_0 + \alpha_1 \Delta SR_t + \alpha_2 X_t + \epsilon_t \\ \Delta SR_t &= \beta_0 + \beta_1 \Delta\left[CR_t\right] + \beta_2 X_t + \eta_t \end{aligned}$$

If we are interested in the effect on firms within group i, then we can decompose the previous system as follows:

$$\begin{aligned} \Delta CR_{i,t} &= \alpha_{0,i} + \alpha_{1,i}\Delta SR_t + \alpha_{2,i} X_t + \epsilon_{i,t} \\ \Delta CR_{-i,t} &= \alpha_{0,-i} + \alpha_{1,-i}\Delta SR_t + \alpha_{2,-i} X_t + \epsilon_{-i,t} \\ \Delta SR_t &= \beta_0 + \beta_1\left[\Delta CR_{i,t}; \Delta CR_{-i,t}\right] + \beta_2 X_t + \eta_t \end{aligned}$$

Substituting $\Delta CR_{-i,t}$ into the expression for ΔSR_t , combining terms and after solving for ΔSR_t, the system of equation can be written as:

$$\Delta CR_{i,t} = \alpha_{0,i} + \alpha_{1,i}\Delta S_t + \alpha_{2,i}X_t + \epsilon_{i,t}$$
$$\Delta S_t = \frac{\beta_0 + \beta_1^{(-i)}\alpha_{0,-i}}{1-\beta_1^{(-i)}\alpha_{1,-i}} + \frac{\beta_1^{(i)}}{1-\beta_1^{(-i)}\alpha_{1,-i}}\Delta CR_{i,t} + \frac{\beta_1^{(-i)}\alpha_{2,-1} + \beta_2^{(i)}}{1-\beta_1^{(-i)}\alpha_{1,-i}}X_t + \frac{\beta_1^{(-i)}\epsilon_{-i,t} + \eta_t}{1-\beta_1^{(-i)}\alpha_{1,-i}}$$

This system is equivalent to the one described in the main text and the differences do not affect the identification assumptions of the analysis. From the previous expression, it is clear that the Rigobon and Sack method still allows to identify the coefficient of interest ($\alpha_{1,i}$).

A.7 Robustness

This section presents different robustness tests to the main analysis in Sections 2.4 and 2.5. Table A.9 shows that the results are robust to different specifications of the variables. In particular, the results are similar when the variables are measured as percentage changes (instead of absolute changes, as in the main text).

Table A.9: Sovereign Risk and Corporate Risk - Percentage Changes

	Dependent Variable: $\%\Delta CR_t$			
	IV	OLS	IV	OLS
$\%\Delta SR_t$	0.1738***	0.1938***	0.1737***	0.1941***
95% CI	[0.085, 0.235]	[0.161, 0.225]	[0.094, 0.238]	[0.168, 0.222]
Controls	No	No	Yes	Yes
Events	29	-	29	-
Obs	486	486	469	469

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of percentage changes in Italian sovereign risk ($\%\Delta SR_t$) on corporate risk ($\%\Delta CR_t$). Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Events are the ones described in subsection 2.3. Controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

Table A.10 show the Rigobon and Sack IV estimates for alternative subsets of event days. Top panel shows the IV estimates when the announcements of only one credit risk agency (either Fitch, Moody's, or Standard & Poor's) are included as events (in addition to the bailout news). Bottom panel shows the IV estimates when excluding different bailout news events. Columns (i) and (ii) show the results when only news about Greek bailouts. Column (iii) shows the estimates when news about austerity packages are excluded from the sample. Column (iv) excludes all the downgrade events. Lastly, column (v) excludes the dates in which the Italian credit rating was downgraded or when the Italian government passed austerity packages, given that some of these dates may coincide with the foreign news events. In all the cases, results are in line with the ones presented in the main text.

Table A.10: Sovereign Risk and Corporate Risk - Alternative Sets of Events

Alternative Set of Downgrade Events

	Dependent Variable: ΔCR_t		
	(i)	(ii)	(iii)
	Moody's	Fitch	S&P
ΔSR_t	0.3068***	0.3396***	0.3767***
95% CI	[0.196, 0.450]	[0.213, 0.478]	[0.284, 0.493]
Controls	Yes	Yes	Yes
Events	23	24	21
Obs	469	469	469

Alternative Set of Bailout News

	Dependent Variable: ΔCR_t				
	(i)	(ii)	(iii)	(iv)	(v)
	Greek Bailouts	Greek 1st Bailout	Ex-Austerity	Ex-Downgrades	Ex-Ita
ΔSR_t	0.3025***	0.2639***	0.2071***	0.3636***	0.2587**
95% CI	[0.157, 0.421]	[0.084, 0.446]	[0.060, 0.431]	[0.263, 0.480]	[0.042, 0.411]
Controls	Yes	Yes	Yes	Yes	Yes
Events	29	18	23	11	28
Obs	456	423	439	401	416

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t). Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Top panel shows the Rigobon and Sack IV estimates when using as events only the announcements of only one credit risk agency (either Fitch, Moody's, or Standard & Poor's) are included as events (in addition to the bailout news). Bottom panel shows the IV estimates when excluding different bailout news events. Column (i) shows the IV estimates when only news about bailouts to Greece are included (in addition to credit rating announcements). Column (ii) shows the estimates when only the first Greek bailout is included. Column (iii) excludes all the events related to news about austerity packages in Greece or Portugal. Column (iv) excludes all the events in which there is a sovereign credit-rating downgrade for Greece or Portugal. Column (v) shows the estimates when excluding days in which the Italian credit rating was downgraded or austerity packages were approved. Controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

Table A.11 compares the IV estimates between the estimator used in the main text

($\hat{\alpha_1}$) and an alternative estimator, $\tilde{\alpha_1}$, which is defined as:

$$\tilde{\alpha_1} = \frac{\Delta\Gamma_{11}}{\Delta\Gamma_{12}} = \frac{var_E\left(\Delta CR_t\right) - var_N\left(\Delta CR_t\right)}{cov_E\left(\Delta CR_t, \Delta SR_t\right) - cov_N\left(\Delta CR_t, \Delta SR_t\right)}$$

Hébert and Schreger (2017) explain that this estimator is based on an "irrelevant instrument". In particular, its denominator is given by the covariance between the change in sovereign risk, which is the variable being instrumented for, and the change in corporate risk, which is the instrument in the case of the $\tilde{\alpha_1}$ estimator.[65] Under the null hypothesis, this covariance is zero which implies that the instrument is irrelevant. Under the null hypothesis, moreover, the $\tilde{\alpha_1}$ estimator is not characterized by standard IV asymptotics. The results in Table A.11 show that the point estimates for $\hat{\alpha_1}$ and $\tilde{\alpha_1}$ are similar. However, the $\tilde{\alpha_1}$ estimator displays wider confidence intervals and the estimates are either not significant or weakly significant.[66]

Table A.11: Sovereign Risk and Corporate Risk - Alternative Estimators

Dependent Variable: ΔCR_t				
	$\hat{\alpha_1}$	$\hat{\alpha_1}$	$\tilde{\alpha_1}$	$\tilde{\alpha_1}$
ΔSR_t	0.288***	0.2903***	0.2799	0.3835
95% CI	[0.175, 0.465]	[0.192, 0.421]	[-0.126, 0.873]	[-0.145, 0.859]
Controls	No	Yes	No	Yes
Events	29	29	29	29
Obs	486	469	486	469
Dependent Variable: $\%\Delta CR_t$				
	$\hat{\alpha_1}$	$\hat{\alpha_1}$	$\tilde{\alpha_1}$	$\tilde{\alpha_1}$
$\%\Delta SR_t$	0.1738***	0.1737***	0.2294**	0.2616*
95% CI	[0.127, 0.238]	[0.125, 0.235]	[0.023, 0.386]	[-0.016, 0.417]
Controls	No	Yes	No	Yes
Events	29	29	29	29
Obs	486	469	486	469

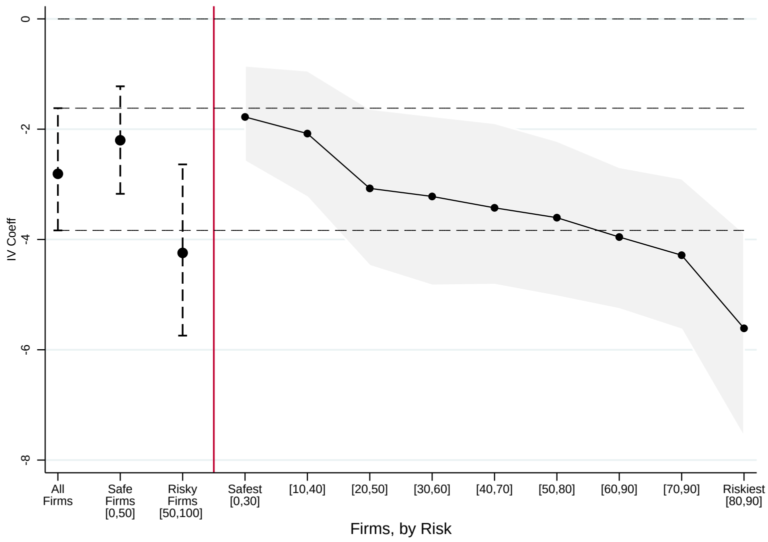
Notes: The table compares alternative IV instruments based on the Rigobon and Sack (2004) framework. Top panel shows the IV estimators of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t). Bottom panel shows the IV estimators of the percentage change of sovereign risk ($\%\Delta SR_t$) on corporate risk ($\%\Delta CR_t$). Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Events are the ones described in subsection 2.3. Controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a studentized stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

[65] See Rigobon and Sack (2004) for an explanation of how this estimator can be implemented in an instrumental variables framework.

[66] The table shows the confidence intervals based on a studentized stratified bootstrap. Under the percentile bootstrap used in the main text, the $\tilde{\alpha_1}$ estimator is not significant in either of the two specifications considered.

To conclude, I next present some robustness tests to the analysis on subsection 2.5. A potential concern regarding the heterogeneous effects across firms described in the main text is that the results may be driven by the different levels in pre-crisis corporate risk across firms. That is, the larger (absolute) change in corporate risk across riskier firms may be simply explained by their larger pre-crisis value. To analyze the robustness of the results, I repeat the same analysis of the main text but using $\%\Delta DD$ as the dependent variable. The advantage of working with $\%\Delta DD$, instead of $\%\Delta CR$, is that the latter measure implies very large swings for those firms whose pre-crisis default risk is almost zero (even for small changes in CR). The $\%\Delta DD$ measure does not have this problem, given that it is typically larger than zero. As shown in Figure A.2 and Table A.12, the results are in line with those described in the main text: firms with higher pre-crisis corporate risk observed a larger percentage decrease in their distance to default.

Figure A.2: IV Coefficients, by Firms with Different Risk



Notes: The figure reports the results for the Rigobon and Sack (2004) IV estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on Mertons' distance to default ($\%\Delta DD_t$), for firms with different pre-crisis risk profiles. The x-axis sorts firms according to their pre-crisis risk profile. The pre-crisis risk is measured as the average distance to default in 2009. Events are the ones described in subsection 2.3. All the regressions include changes in S&P 500 and the VIX index as global controls. Sample period includes April 2010 - April 2012. Grey area depicts the 90 percent confidence intervals, which are computed based on a percentile stratified bootstrap.

Table A.12: Dependent Variable: $\%\Delta DD$

	(1)	(2)	(3)	(4)
Δ Italian CDS	-7.6226***	-7.7132***	-8.0489***	-8.0427***
	(2.2881)	(2.4410)	(1.0816)	(0.8383)
Δ Italian CDS $\times$ DD 2009	1.0721**	1.1089*	1.1491***	1.1705***
	(0.5457)	(0.5780)	(0.1600)	(0.0935)
Δ Italian CDS $\times$ log(Assets) 2009				-0.4660*
				(0.2292)
Δ Italian CDS $\times$ Leverage 2009				2.7788**
				(1.1281)
Δ Italian CDS $\times$ Foreign Sales 2009				-0.0014
				(2.2036)
Observations	36,294	35,115	31,646	31,646
Global Controls	No	Yes	Yes	Yes
Firm Controls	No	No	Yes	Yes

Notes: Table presents OLS estimates of the effect of changes in Italian sovereign risk (ΔSR_t) on Merton's distance to default ($\%\Delta DD_{i,t}$), for a panel of publicly traded Italian firms. The variables log assets, leverage, and share of foreign sales are expressed as deviations from the 2009 mean across all the firms in the sample. Global controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors are clustered at the industry level. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

A.8 Identification Challenges: Further Analysis

This section presents additional tests to back up the identifying assumptions and to further explore the potential role of common factors behind the results described in the main text. First, to explore changes in the market price of risk across Europe, I analyze whether the option-implied volatility for an index of European industrial firms is affected by the "foreign news events" captured in this paper. Second, to study the role of global investors, I study whether the results hold for a subsample of Italian firms that are only traded in a domestic stock exchange and, therefore, are arguably less exposed to foreign investors. Third, I present the Rigobon and Sack IV estimates based on an endogenous classification of events that allows to shed light on whether the market anticipated or not the events described in the main text. Finally, I study whether the cross-country differences can be explained by the pre-crisis levels of risk.

The analysis in Table A.13 shows that the option-implied volatility for an index of European industrial firms is not affected by the foreign news events. The table presents the OLS and Rigobon and Sack IV estimates of the effect of changes in Italian sovereign risk on two different European-level measures. The first two panels show the results for a broad price index of European industrial firms (STOXX Europe 600 Industrials index). The last two panels present the estimates for the option-implied volatility of that same index. The OLS estimates show that an increase in Italian sovereign risk is associated with a significant decrease in the price of the European index and with an increase in its implied-volatility. For instance, a 1pp increase in Italian CDS leads to a 7.5% increase in the implied-volatility of the index. The Rigobon and Sack IV estimates, however, are not significant. The results, thus, suggest that changes in (Italian) sovereign risk are associated with changes in the market price of risk in Europe but the foreign news events described in the main text are not behind these changes.

Table A.13: Sovereign Risk and Implied Volatility

	Dependent Variable			
	STOXX Europe 600 Industrials		Implied Volatility	
	IV	OLS	IV	OLS
ΔSR_t	-1.9496	-5.8127***	-0.2693	7.4866***
95% CI	[-5.684, 2.191]	[-6.997, -4.632]	[-8.627, 8.149]	[5.379, 9.851]
Controls	Yes	Yes	Yes	Yes
Events	29	-	29	-
Obs	474	474	470	470

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on two different European-level measures: (i) the STOXX Europe 600 Industrials (goods & services) and (ii) the option-implied volatility of that index. Measures (i) and (ii) are expressed as percentage changes. Sovereign risk is based on the annualized CDS spread for Italy. Events are the ones described in the subsection 2.3. Global controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

To understand the potential role of global investors, I focus on a subset of "local" corporate Italian firms that trade in the ISE (Italian Stock Exchange) but are not traded in any other foreign index. Arguably, these firms are less exposed to international investors and rely more on the domestic financial institutions to finance their borrowing needs. Table A.14 shows the Rigobon and Sack IV estimates for the subsample of local firms. Results are in line with those presented in the main text.

Table A.14: Sovereign Risk and Corporate Risk - Local Firms

	Dependent Variable: ΔCR_t			
	IV	OLS	IV	OLS
ΔSR_t	0.224***	0.3048***	0.2146***	0.315***
95% CI	[0.070, 0.365]	[0.234, 0.365]	[0.101, 0.335]	[0.266, 0.367]
Controls	No	No	Yes	Yes
Events	29	-	29	-
Obs	486	486	469	469

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t). Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Only Italian firms that trade exclusively in the ISE (Italian Stock Exchange) are included. Events are the ones described in the subsection 2.3. Global controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

An important assumption behind the identification strategy is that markets do not fully anticipate the foreign news events. If they do, then these events are not suitable to capture exogenous variation in sovereign risk. As investors may have partially anticipated some of these news (particularly news regarding sovereign downgrades), I consider here an alternative definition of events based on the volatility of the 10-year Greek CDS. I classify as events those days in which the 3-day rolling window standard deviation of the Greek CDS was higher than the 90^{th} percentile.[67] A potential caveat of this endogenous identification of events is that changes in the volatility of Greek sovereign risk may potentially reflect changes in the underlying fundamentals of Italy (or, more broadly, Europe) that are transmitted to Greek sovereign bonds via contagion, making the identification analysis problematic. For this reason, the regressions in Table A.15 include the change in the STOXX Europe 600 Industrials as an additional control (as well as the SP and VIX indexes). When these controls are included, the results are in line with the ones presented in the main text suggesting that markets did not fully anticipate the foreign news events used in the analysis. In the absence of controls, however, the estimates are slightly larger than in the baseline model, suggesting that the volatility in Greek CDS may also be capturing "global" events that affect Europe.

Table A.15: Sovereign Risk and Corporate Risk - Endogenous Events

	Dependent Variable: ΔCR_t			
	IV	OLS	IV	OLS
ΔSR_t	0.3939***	0.3666***	0.2139**	0.1932***
95% CI	[0.219, 0.537]	[0.288, 0.438]	[0.003, 0.387]	[0.148, 0.237]
Controls	No	No	Yes	Yes
Events	21	-	21	-
Obs	487	487	471	471

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t). Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Event days are those in which the 3-day rolling window standard deviation of the Greek CDS was higher than the 90^{th} percentile. Controls refers to changes in S&P 500, the VIX index, and the STOXX Europe 600 Industrials (goods & services). Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denotes significance at 1%, 5%, and 10%, respectively.

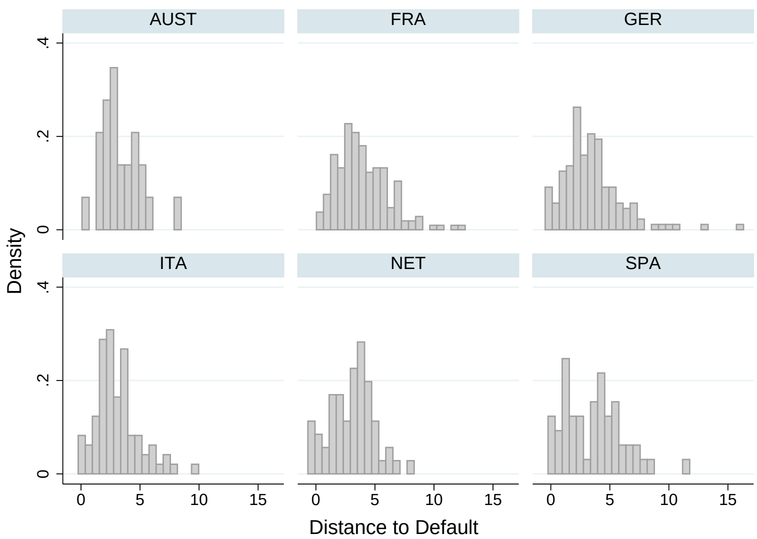
Lastly, I study whether the cross-country differences are driven by the pre-crisis levels of risk. The concern is that the identification strategy may be invalidated if Italian firms have a larger pre-crisis level of corporate risk relative to other European countries. If that is the case, the foreign news events may impact more on Italian firms purely because of their higher pre-crisis risk. Based on the 2009 year, Figure A.3 shows the risk distribution

[67]The methodology is similar to the one used in Mink and de Haan (2013). I choose the 90^{th} percentile as a cutoff in order to have a similar number of events as in the baseline model. The Levene (1960) and Brown and Forsythe (1974) test strongly reject the hypothesis of equal variances for ΔSR_t across event and non-event days.

of the European firms in the sample. The figure highlights that the pre-crisis risk profile of the Italian firms is in line with the risk profiles observed in other European countries.

To analyze the role of pre-crisis corporate risk more formally, Table A.16 shows the Rigobon and Sack IV estimates for different subsamples of Italian and German firms. The analysis allows to compare firms located in Italy and Germany with similar pre-crisis levels of corporate risk. The top panel shows the IV estimates for firms with a 2009 average corporate risk below 2%, between 1-3%, and above 3%. The results suggest that differences in pre-crisis corporate risk are not driving the results presented in the main text. In particular, even for the riskier subset of German firms, the Rigobon and Sack IV estimates are not significant. The middle and bottom panels show the same IV estimates but the sorting of firms is done based on their average corporate risk in 2010 and 2011, respectively. Even with this sorting, the IV estimates for the German firms are not significant.

Figure A.3: Pre-crisis Corporate Risk across Europe



Notes: Figure shows the distribution of pre-crisis corporate risk for six European countries. The measure of corporate risk is based on Merton's distance-to-default measure and corresponds to 2009. A lower distance to default implies a higher corporate risk.

Table A.16: Sovereign Risk and Corporate Risk - Different Pre-crisis CR

	Dependent Variable: ΔCR_t					
	Italy			**Germany**		
	CR=[0-2]	**CR=[1-3]**	**CR>3**	**CR=[0-2]**	**CR=[1-3]**	**CR>3**
			Base year: 2009			
ΔSR_t	0.0556	0.2979**	0.9196***	0.0112	0.099	0.1892
95% CI	[-0.037, 0.188]	[0.063, 0.557]	[0.568, 1.504]	[-0.035, 0.062]	[-0.076, 0.321]	[-0.394, 0.813]
			Base year: 2010			
ΔSR_t	0.0875*	0.5081**	0.9519***	0.0273	0.1945	0.2162
95% CI	[-0.006, 0.208]	[0.044, 1.145]	[0.502, 1.747]	[-0.026, 0.081]	[-0.164, 0.556]	[-0.641, 0.937]
			Base year: 2011			
ΔSR_t	0.0174	0.4046***	0.8361***	0.0282	0.2864	0.2264
95% CI	[-0.047, 0.087]	[0.165, 0.873]	[0.528, 1.429]	[-0.025, 0.092]	[-0.151, 0.736]	[-0.489, 0.991]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Events	29	29	29	29	29	29
Obs	469	469	469	469	469	469

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t) of Italian and German firms. Sovereign risk is based on the annualized CDS spread for Italy. Corporate risk is computed using Merton's distance-to-default framework. Top panel shows the results for a subsample of firms with an average 2009 CR below 2%, between 1-3%, and above 3%. The middle and bottom panels show the same results but the classification is based on the years 2010 and 2011, respectively. Events are the ones described in the subsection 2.3. Controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

A.9 Results for Risk-Neutral Default Probabilities

The goal of this section is to create a mapping between the empirical estimates reported in the main text and the calibration of the quantitative model. Along Section 2, I use (annual) CDS of the Italian government as a measure of sovereign risk. This measure, however, differs from the risk-neutral default probability of the quantitative model, as implied by the sovereign risk process in equations (4.18) and (4.19).

To create this mapping, I repeat the Rigobon and Sack (2004) IV estimation described in the main text, but using the quarterly risk-neutral default probability instead of annual CDS spreads as a measure of sovereign risk. Under some simplifying assumptions (see White, 2013) the risk-neutral default probability (P) implied from the CDS can be approximated as:

$$P_t = 1 - e^{\frac{-S_t \times T}{1-RR}} \tag{A.1}$$

where S_t is the (annualized) CDS spread, T are years to maturity, and RR is the recovery rate. I set RR to 54%, which is the recovery rate on government's bonds implied by the quantitative model and $T = 0.25$, as the model is calibrated at a quarterly frequency.

Table A.17 reports the Rigobon and Sack IV estimates when using P_t as the measure of sovereign risk.

Table A.17: Sovereign Risk and Corporate Risk

	Dependent Variable: ΔCR_t (quarterly)			
	IV	OLS	IV	OLS
ΔP_t	0.1332***	0.1695***	0.1341***	0.1729***
95% CI	[0.057, 0.204]	[0.134, 0.202]	[0.072, 0.189]	[0.147, 0.200]
Controls	No	No	Yes	Yes
Events	29	-	29	-
Obs	486	486	469	469

Notes: The table reports the results for the Rigobon and Sack (2004) IV estimator and for the OLS estimator of the effect of changes in Italian sovereign risk (ΔSR_t) on corporate risk (ΔCR_t). Sovereign risk is based on the quarterly risk-neutral default probability for the Italian government, computed from CDS spreads data. Corporate risk is also in quarterly terms and it is computed using Merton's distance-to-default framework. Events are the ones described in the subsection 2.3. Controls refers to changes in S&P 500 and the VIX index. Sample period includes April 2010 - April 2012. Standard errors and confidence intervals are computed based on a percentile stratified bootstrap. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

B The Role of Bank-Lending Channel: Additional Material

B.1 Definition of Variables

This section describes how the variables used in Section 3 are constructed. All the bank-specific variables come from the *BilBank 2000* database distributed by ABI (the Italian Banking Association). The data include annual balance-sheet information for commercial, cooperative, and popular banks headquartered in Italy during the 2005-2013 period. The main variables used in the analysis are summarized in Table B.1 and are: *log Assets, Sovereign Exposure, Loans, Non-Fin Loans, NPLs, Non-Fin NPLs, Liquid Assets, Retail Funding, Net Worth, Profits,* and *Reserves*.

For each of the banks in the dataset, I extract the following variables relative to the assets of the banks: total assets, risk-weighted assets, sovereign bond holdings, liquid assets (cash), total loans, loans to non-financial firms, bad loans, and substandard loans. I use *Log Assets* to proxy for the size of the bank. *Sovereign Exposure* is defined as the ratio between sovereign bond holdings and risk-weighted assets.[68] *Loans* represents the ratio of total loans to total assets. *Non-Fin Loans* is the share of loans to the non-financial sector, relative to total loans. *NPLs* is defined as the sum of bad loans and substandard loans. *Non-Fin NPLS* is defined analogously but including only loans to non-financial firms. I also extract the following data regarding banks' liabilities and net worth: payables to customers, bank reserves, bank net worth, and operating profit (loss) for the year. I define *Retail Funding* as the ratio between payables to customers and total assets. *Net Worth* and *Reserves* are defined as the ratio of bank net worth and bank reserves to total assets, respectively. *Profits* are risk-adjusted and they are defined as the ratio of operating profit to risk-weighted assets. Table B.1 provides summary statistics for these variables.

For the results presented in the robustness section, I also obtain the following data from the ABI dataset: assets held for trading, assets for sale, payables to other banks, bank's capital and Tier1. Using this information, I compute the following variables. *Securities* is the sum of assets held for trading and assets for sale over risk-weighted assets. *Bank Funding* is the ratio of payables to other banks and total assets. *Capital* is defined as the bank's capital over total assets. The *Tier1* variable is the one reported in the ABI dataset.

[68] This is the standard in the literature. See for instance, Bottero et al. (2020).

Table B.1: Summary Statistics

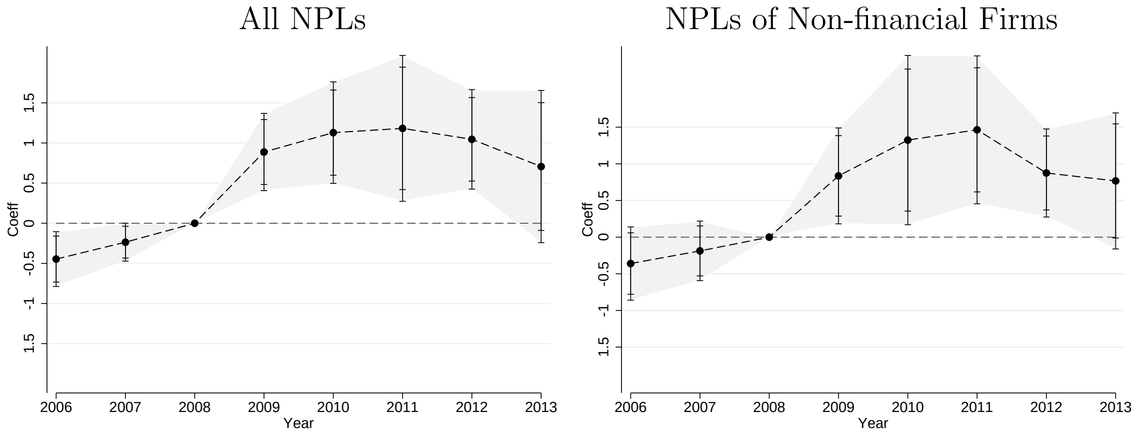
Variable	Mean	SD	Pc10	Pc90
log Assets	13.16	1.69	11.26	15.63
Sovereign Exposure	0.192	0.193	0.003	0.441
Loans	0.683	0.154	0.487	0.839
Non-Fin Loans	0.639	0.149	0.460	0.789
NPLs	0.045	0.032	0.012	0.092
Non-Fin NPLs	0.053	0.041	0.012	0.109
Liquid Assets	0.011	0.008	0.004	0.020
Retail Funding	0.492	0.142	0.347	0.685
Net Worth	0.109	0.042	0.063	0.163
Profits	0.008	0.014	0.001	0.019
Reserves	0.076	0.052	0.007	0.146

Notes: Variables are measured at the end of 2008. Sovereign exposure, loans, liquid assets, retail funding, net worth, profits, and reserves are expressed in terms of banks (risk-weighted) assets. Non-performing loans (NPLs) are expressed in terms of banks loans. Loans to non-financial firms are expressed as a fraction of banks' loans.

B.2 Additional Results

I conduct different tests to asses the robustness of the main results presented in subsection 3.3. I start by showing that results are robust to alternative specifications of the dependent variable. Figure B.1 shows the results for the log change in NPLs ($\Delta log(NPLS)$), which (unlike the variable used in the main analysis) is not bounded in the $[-2, 2]$ interval and therefore does not limit the influence of potential outliers. The estimated coefficients are in line with the ones presented in the main analysis (if anything, they are slightly larger in magnitude).

Figure B.1: Sovereign Exposure and NPLs - Dep. Variable: $\Delta log(NPLS)$



Notes: Figures reports the OLS estimates for the $\beta_{1,h}$ coefficient in equation (3.1). The dependent variable is: $log(NPLs_{i,j,h}) - log(NPLs_{i,j,2008})$. The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). To construct the CI, standard errors are clustered at the regional level. The set of controls include: bank size (as measured by log assets), loans, liquid assets, retail funding, net worth, profits, and reserves. For the right-hand-side panel, the share of loans to non-financial firms is also included as a control. Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks.

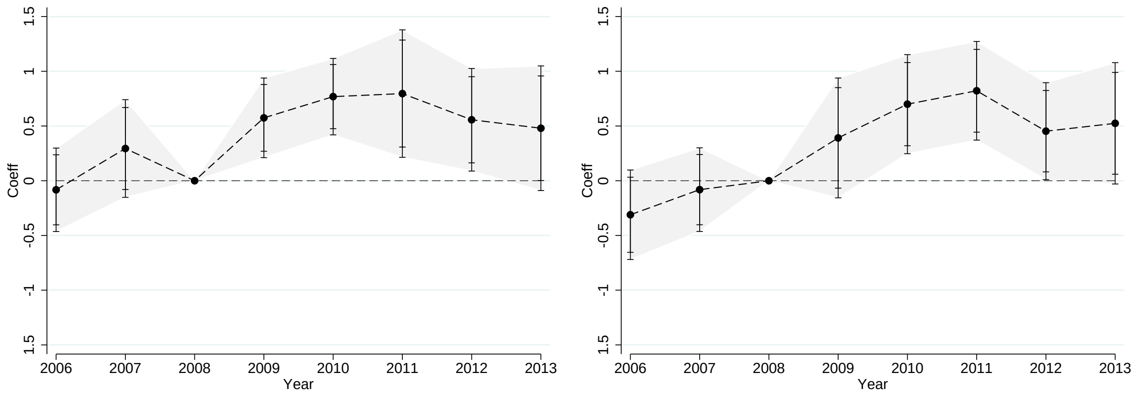
I next analyze the results when the dependent variable is measured as the ratio between NPLs and bank's loans. To do this, the left-hand-side variable of equation (3.1) is replaced with:

$$\%\Delta\left(\frac{NPLS}{Loans}\right)_{i,j,(2008+h)} = \frac{\left(\frac{NPLS}{Loans}\right)_{i,j,(2008+h)} - \left(\frac{NPLS}{Loans}\right)_{i,j,2008}}{0.5 \times \left(\left(\frac{NPLS}{Loans}\right)_{i,j,(2008+h)} + \left(\frac{NPLS}{Loans}\right)_{i,j,2008}\right)}$$

Figure B.2 presents the results. Arguably, this is a better measure of the change in bank's portfolio quality as it measures the changes in NPLs relative to changes in bank's loans. For instance, for a bank that did not exhibit an increase in its NPLs, this variable still captures a deterioration in the quality of the bank's portfolio to the extent that the bank reduced its credit supply. As expected, the magnitude of the estimates in Figure B.2 is slightly larger than the one described in the main text.

Figure B.2: Sovereign Exposure and NPLs - Dep. Variable: $\%\Delta\left(\frac{NPLS}{Loans}\right)$

All NPLs | NPLs of Non-financial Firms



Notes: Figures report the OLS estimates for the $\beta_{1,h}$ coefficient in equation (3.1). The dependent variable is $\%\Delta\left(\frac{NPLS}{Loans}\right)_{i,j,2008+h}$. The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). To construct the CI, standard errors are clustered at the regional level. The set of controls includes: bank size (as measured by log assets), loans, liquid assets, retail funding, net worth, profits, and reserves. For the right-hand-side panel, the share of loans to non-financial firms is also included as a control. Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks.

Table B.2 reports the estimates for different sets of bank controls, X_t, and shows that the results are robust to different specifications (column 6 is the baseline specification). The analysis in columns (1)-(6) highlights the importance of controlling for relevant bank-level factors that may correlate with both their sovereign exposure and the risk profile of their loans. Ignoring these controls leads to a non significant relation between sovereign exposures and NPLs. Only after the vector X_t is expanded to include variables describing the bank's assets, liabilities, and capital structure, is the relation positive and significant. Columns (7)-(10) present the results when adding other bank characteristics, such as holding of securities, bank funding, capital, and Tier 1. All the results are robust to the addition of these other characteristics.

Table B.2: Dependent Variable: %Δ NPLs (non-financial)

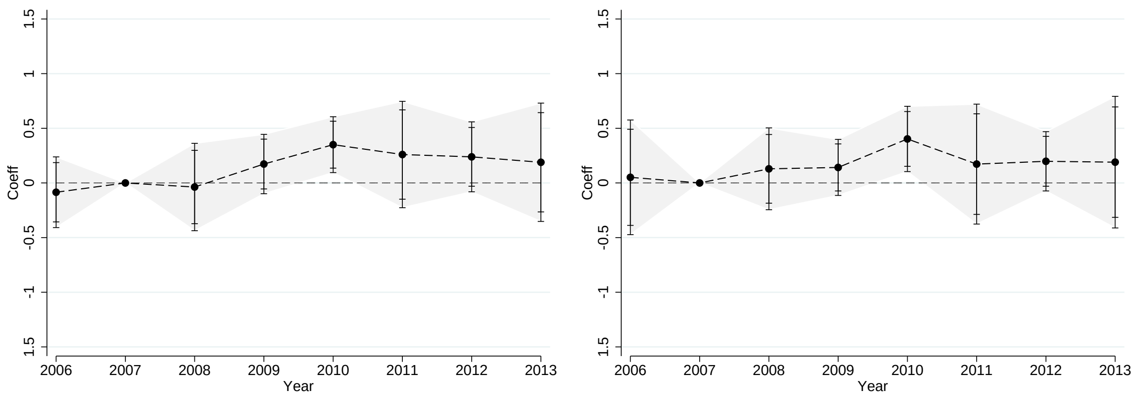
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sov Exposure	-0.1095	0.4457	0.4490*	0.5197*	0.7661***	0.7520***	0.7291***	0.7223***	0.7282***	0.6827***
	(0.3248)	(0.2606)	(0.2561)	(0.2558)	(0.2455)	(0.2345)	(0.2292)	(0.2403)	(0.2445)	(0.2385)
log(Assets)	0.0431	0.0603**	0.0640**	0.0530**	0.0248	0.0187	0.0144	0.0074	0.0303	0.0195
	(0.0381)	(0.0235)	(0.0229)	(0.0222)	(0.0277)	(0.0279)	(0.0282)	(0.0255)	(0.0265)	(0.0240)
Liquidity		2.6063	1.1738	1.6157	-0.6539	-1.0332	-0.9702	-0.8999	-1.0222	-0.8777
		(5.4434)	(5.0789)	(5.4447)	(4.9631)	(5.2978)	(5.3123)	(5.4081)	(5.3486)	(5.4282)
Loans		1.0482***	1.0952***	1.0431**	1.2309***	1.1042***	1.2708***	1.3140***	1.1566***	1.4022***
		(0.3215)	(0.3203)	(0.3657)	(0.3956)	(0.3446)	(0.3955)	(0.4079)	(0.2755)	(0.3328)
Non-fin Loans		0.6865	0.7232	0.7755*	0.7191	0.7735	0.7584	0.7671	0.7144	0.7061
		(0.4273)	(0.4470)	(0.4378)	(0.4363)	(0.4730)	(0.4432)	(0.4444)	(0.4596)	(0.4273)
Retail Funding			0.3179	0.3219	0.3223	0.2446	0.2803	0.4079	0.1907	0.3446
			(0.2839)	(0.2719)	(0.2730)	(0.2338)	(0.2592)	(0.2762)	(0.2000)	(0.2620)
Net Worth				-1.8370*	1.1931	0.7350	0.9209	1.0069		
				(1.0034)	(1.1036)	(1.2533)	(1.2651)	(1.2297)		
Reserves					-4.3570***	-4.5667***	-4.7064***	-4.5366***	-2.7765	-2.6083
					(1.4682)	(1.5070)	(1.5189)	(1.5750)	(1.6539)	(1.7035)
Profit						5.2966*	7.1480*	7.1924*	5.9350**	8.3461**
						(2.6862)	(3.9375)	(3.9210)	(2.1359)	(3.3069)
Securities							0.2924	0.2723		0.3402
							(0.2206)	(0.2317)		(0.2018)
Bank Funding								0.3727		0.3278
								(0.3193)		(0.3389)
Capital									3.1733	3.3915*
									(1.8459)	(1.8168)
Tier1									-0.0002	0.0006
									(0.0108)	(0.0106)
Observations	419	419	419	419	419	419	419	419	419	419
Adjusted R^2	0.120	0.179	0.179	0.186	0.234	0.239	0.240	0.240	0.247	0.250
Regional Dummy?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the OLS estimators of the model in equation (3.1) for different specifications of the controls. Results are for the 2011 year only. Dependent variable is the $\%\Delta NPLs$, as defined in equation (3.2). Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks. Only NPLs of the non-financial sector are included. All the specifications include regional-level dummies. Standard errors are clustered at the regional level. ***, **, *, denote significance at 1%, 5%, and 10%, respectively.

To provide further evidence supporting the parallel trend assumption, I repeat the main analysis but using 2007 as the base year. The main goal is to assess whether the 2007 banks' sovereign holdings have any implications on the growth rate of NPLs during 2008, the year of the global financial crisis. This exercise allows to shed some light on the validity of the parallel trend assumption because NPLs increased sharply during 2008 but Italian sovereign spreads did not increase until mid-2009. The results reported in Figure B.3 show that the growth rate of NPLs during 2008 is not related to the 2007 banks' holdings of sovereign debt, providing evidence in favor of the identification assumption: banks' with higher sovereign exposure were not taking more risk than their low exposure peers (after controlling for all the other banks' characteristics). Under the 2007 base year, however, notice that the estimates for the 2010-2012 period are more noisy than the ones presented in the main analysis (and only significant for 2010). Overall, these results may be pointing out an important re-balancing of banks' portfolios during 2008.

Figure B.3: Sovereign Exposure and NPLs - 2007 as Base Year

All NPLs | NPLs of Non-financial Firms



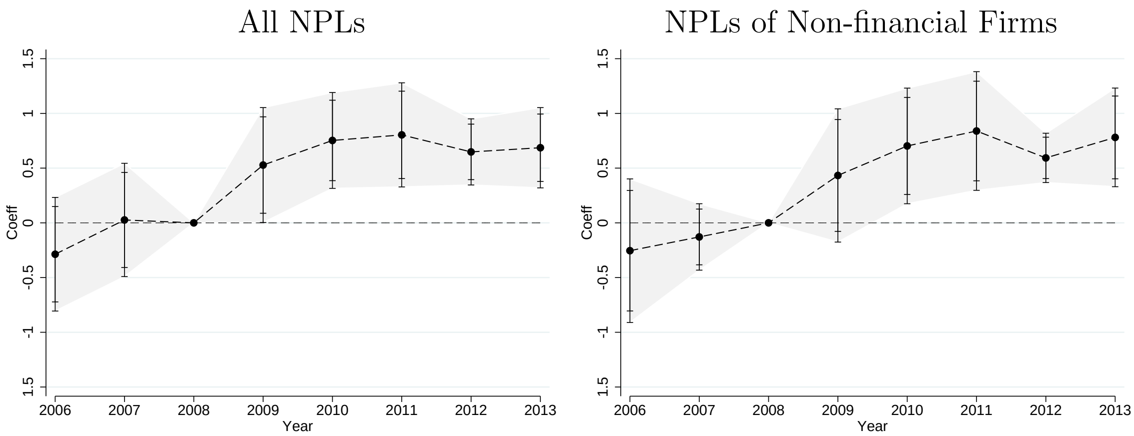
Notes: Figures report the OLS estimates for the $\beta_{1,h}$ coefficient in equation (3.1), but using 2007 (instead of 2008) as the base year. Dependent Variable: $\%\Delta NPLs_{i,j,h}$ as defined in equation (3.2). The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). Banks are aggregated at the five Italian macro-regions: North-West, North-East, Central, South, and Islands. Clustered standard errors at the regional level are used to construct the CI. The set of controls includes: bank size (as measured by log assets), loans, liquid assets, retail funding, net worth, profits, and reserves. For the right-hand-side panel, the share of loans to non-financial firms is also included as a control. Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks.

As banks may be operating across different regions and not only in the region where its headquarters are located, Figure B.4 reports the macro-region-level OLS estimates, for different horizons h.[69] Instead of assuming that banks operate exclusively in the region of their headquarters, I sort banks across a broader category of regions. In particular, each bank is sorted into one of the five Italian macro-regions (North-West, North-East, Central, South, and Islands) and I assume that it operates exclusively within that region. All the

[69]This analysis complements the one in Table 3.2 in the main text.

estimates are in line with those associated to the finer aggregation level. If anything, this level of aggregation displays a larger persistence in the estimated effects.

Figure B.4: Sovereign Exposure and NPLs - Macro Regions



Notes: Figures report the OLS estimates for the $\beta_{1,h}$ coefficient in equation (3.1). Dependent Variable: $\%\Delta NPLs_{i,j,h}$ as defined in equation (3.2). The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). Banks are sorted at the five Italian macro-regions: North-West, North-East, Central, South, and Islands. Clustered standard errors at the macro-regional level are used to construct the CI. The set of controls includes: bank size (as measured by log assets), loans, liquid assets, retail funding, net worth, profits, and reserves. For the right-hand-side panel, the share of loans to non-financial firms is also included as a control. Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks.

C The Quantitative Model: Additional Material

C.1 Characterization of Bank's Solution and Pricing Kernels

This section provides a proof for expressions (4.13)-(4.15) in the main text, following similar steps to those in Gertler and Karadi (2011) and Bocola (2016). The first step is to guess that the value function is a linear function of bank's net worth: $W(\eta, S) = \alpha(S) \times \eta$. After replacing this guess into the right-hand side of the Bellman equation in (4.12), we get:

$$
\begin{aligned}
&W(\eta, S) = Max_{x', B', b'(.)}\ \tilde{\beta}\mathbb{E}\left[(1-\psi)\eta' + \psi\alpha(\boldsymbol{S'})\eta'\right] \\
&\text{subject to} \\
&\qquad \frac{1}{R_f}x' + \eta = \int q\left(., \boldsymbol{S}\right) b'(., \boldsymbol{S}) d\Omega + q_B(\boldsymbol{S})B' \\
&\qquad \eta' = -x' + \int \mathbb{R}_f(., \boldsymbol{S'}) b'(., \boldsymbol{S}) d\Omega + \mathbb{R}_G(\boldsymbol{S'})B' \\
&\qquad \kappa\left(\int q(., \boldsymbol{S}) b'(., \boldsymbol{S}) d\Omega + q_B(\boldsymbol{S})B'\right) \leq \alpha(\boldsymbol{S})\eta \\
&\qquad \boldsymbol{S'} = H\left(\boldsymbol{S}\right)
\end{aligned}
$$

Let $\Lambda(\boldsymbol{S'}) = (1-\psi) + \psi\alpha(\boldsymbol{S'})$. After replacing the balance sheet into the law of motion for net worth, the previous Bellman equation can be written as:

$$
W(\eta, S) = Max_{x', B', b'(.)}\ \tilde{\beta}\mathbb{E}\left[\Lambda(\boldsymbol{S'})\eta'\right] \tag{C.1}
$$

subject to

$$
\begin{aligned}
&\eta' = R_f\eta + \int \left[\mathbb{R}_f(., \boldsymbol{S'}) - R_{rf}q\left(., \boldsymbol{S}\right)\right] b'(., \boldsymbol{S}) d\Omega + \left[\mathbb{R}_G(\boldsymbol{S'}) - R_{rf}q_B\left(\boldsymbol{S}\right)\right] B \\
&\kappa\left(\int q(., \boldsymbol{S}) b'(., \boldsymbol{S}) d\Omega + q_B(\boldsymbol{S})B'\right) \leq \alpha(\boldsymbol{S})\eta \\
&\boldsymbol{S'} = H\left(\boldsymbol{S}\right)
\end{aligned}
$$

The first order conditions with respect to $b'(k, b, z)$ (for each idiosyncratic state) and B', and the slackness condition (assuming an interior solution for all the variables) are given by:

$$
\tilde{\beta}\mathbb{E}\left(\Lambda(\boldsymbol{S'})\left[\mathbb{R}_f(., \boldsymbol{S'}) - R_f q\left(., \boldsymbol{S}\right)\right]\right) - \mu\left(\boldsymbol{S}\right)\kappa q(., \boldsymbol{S}) = 0 \tag{C.2}
$$

$$
\tilde{\beta}\mathbb{E}\left(\Lambda(\boldsymbol{S'})\left[\mathbb{R}_G(\boldsymbol{S'}) - R_f q_B\left(\boldsymbol{S}\right)\right]\right) - \mu\left(\boldsymbol{S}\right)\kappa q_B(\boldsymbol{S}) = 0 \tag{C.3}
$$

$$
\mu\left(\boldsymbol{S}\right)\left[\kappa\left[\int q\left(., \boldsymbol{S}\right) b'(.) d\Omega + q_B(S)B'\right] - \alpha\left(\boldsymbol{S}\right)\eta\right] = 0 \tag{C.4}
$$

where $\mu(\boldsymbol{S}) \geq 0$ is the Lagrange multiplier of the leverage constraint. Multiplying both sides of equation (C.2) by $b'(., \boldsymbol{S})$, integrating across all firms, and rearranging terms:

$$\mu(\boldsymbol{S})\,\kappa \int b'(., \boldsymbol{S})\, q(., \boldsymbol{S}) d\Omega = \tilde{\beta}\mathbb{E}\left(\Lambda(\boldsymbol{S'}) \int \left[\mathbb{R}_f(., \boldsymbol{S}') - R_f q(., \boldsymbol{S})\right] b'(., \boldsymbol{S})\, d\Omega\right)$$

Similarly, after multiplying both sides of (C.3) by B' and rearranging terms, we get:

$$\mu(\boldsymbol{S})\,\kappa q_B(\boldsymbol{S}) B' = \tilde{\beta}\mathbb{E}\left(\Lambda(\boldsymbol{S'})\left[\mathbb{R}_G(\boldsymbol{S}') - R_f q_B(\boldsymbol{S})\right]\right) B'$$

Summing both sides of the last two expressions, and replacing with the law of motion of net worth and the slackness condition:

$$\tilde{\beta}\mathbb{E}\left[\Lambda(\boldsymbol{S'})\,\eta'\right] = \left\{\mu(\boldsymbol{S})\,\alpha(\boldsymbol{S}) + \tilde{\beta}R_f\mathbb{E}\left[\Lambda(\boldsymbol{S'})\right]\right\}\eta \tag{C.5}$$

According to the initial guess (at the optimal solution): $W(\eta, \boldsymbol{S}) \equiv \tilde{\beta}\mathbb{E}\left[\Lambda(\boldsymbol{S'})\,\eta'\right] = \alpha(\boldsymbol{S})\,\eta$. Replacing this expression in (C.5), we get that the initial guess is verified for:

$$\alpha(\boldsymbol{S}) = \tilde{\beta}R_f \frac{\left[(1-\psi) + \psi\mathbb{E}\alpha(\boldsymbol{S'})\right]}{1-\mu(\boldsymbol{S})} \tag{C.6}$$

Replacing equation (C.6) in the slackness condition, we obtain the Lagrange multiplier:

$$\mu(\boldsymbol{S}) = Max\left\{1 - \frac{\tilde{\beta}R_f\left[(1-\psi) + \psi\mathbb{E}\alpha(\boldsymbol{S'})\right]}{\kappa\left[\int q(., \boldsymbol{S})\, b'(.)d\Omega + q_B(\boldsymbol{S})B'\right]}\eta\,,\, 0\right\} \tag{C.7}$$

Banks' Stochastic Discount Factor and Pricing Kernels

From the first order conditions in (C.2) and (C.3), solving for $q(., \boldsymbol{S})$ and $q_B(\boldsymbol{S})$:

$$q(., \boldsymbol{S}) = \frac{\tilde{\beta}\mathbb{E}\Lambda(\boldsymbol{S'})\mathbb{R}_f(., \boldsymbol{S}')}{\mu(\boldsymbol{S})\,\kappa + \tilde{\beta}R_f\mathbb{E}\left(\Lambda(\boldsymbol{S'})\right)} \tag{C.8}$$

$$q_B(\boldsymbol{S}) = \frac{\tilde{\beta}\mathbb{E}\Lambda(\boldsymbol{S'})\mathbb{R}_G(\boldsymbol{S}')}{\mu(\boldsymbol{S})\,\kappa + \tilde{\beta}R_f\mathbb{E}\left(\Lambda(\boldsymbol{S'})\right)} \tag{C.9}$$

We can therefore define the bank's stochastic discount factor (SDF) as:

$$\Xi(\boldsymbol{S'}, \boldsymbol{S}) \equiv \frac{\tilde{\beta}\Lambda(\boldsymbol{S'})}{\mu(\boldsymbol{S})\,\kappa + \tilde{\beta}R_f\mathbb{E}\left(\Lambda(\boldsymbol{S'})\right)}$$

Notice that the bank's discount factor does not only depend on whether its leverage constraint is currently binding or not, but it also depends on next-period's aggregate state $\boldsymbol{S'}$. News affecting sovereign and corporate risk, even when they do not lead to a binding leverage constraint, may still affect the bank's current SDF as they affect the likelihood that the constraint may bind in the future. Replacing with the definition of the bank's stochastic discount factor and the definitions of $\mathbb{R}_f(,\boldsymbol{S})$ and $\mathbb{R}_G(\boldsymbol{S})$ in equations (C.8) and (C.9), we can write the pricing kernels as follows:

$$q(k',b',z,\boldsymbol{S}) = \mathbb{E}\Bigg[\varXi(\boldsymbol{S'},\boldsymbol{S})\Bigg([1-h(k',b',z',\boldsymbol{S'})]\times M_f(k',b',z',\boldsymbol{S'})+ \\ + h(k',b',z',\boldsymbol{S'})\times R(k',b',z')\Bigg)\Bigg]$$

and

$$q_B(\boldsymbol{S}) = \mathbb{E}\left[\varXi(\boldsymbol{S'},\boldsymbol{S})\left([1-h_G(\boldsymbol{S'})]\times M_G(\boldsymbol{S'}) + h_G(\boldsymbol{S'})\times q_B(\boldsymbol{S'})\frac{B}{B'}\right)\right]$$

with $M_f(k',b',z',\boldsymbol{S}') \equiv (1-m_f)(c_f+q(k'',b'',z',\boldsymbol{S'}))+m_f$, and $k''\equiv k'(k',b',z',\boldsymbol{S}')$ and $b''\equiv b'(k',b',z',\boldsymbol{S}')$ denote the next-period firm's optimal policy functions. Also, $M_G(\boldsymbol{S'})\equiv(1-m_G)(c_G+q_B(\boldsymbol{S'}))+m_G$.

C.2 Model-implied TFP

The model described in Section 4 assumes, for simplicity, only one source of aggregate uncertainty: a shock to the government's default probability. Instead of modeling the aggregate TFP process, I consider a reduced-form productivity loss in the event of a government default. In particular, I assume that while the government is in default, aggregate productivity is given by $\xi_D < \xi_{ND} = 1$. This assumption links firms' expected productivity with sovereign risk and it is flexible enough to match the increase in corporate risk caused by sovereign risk.

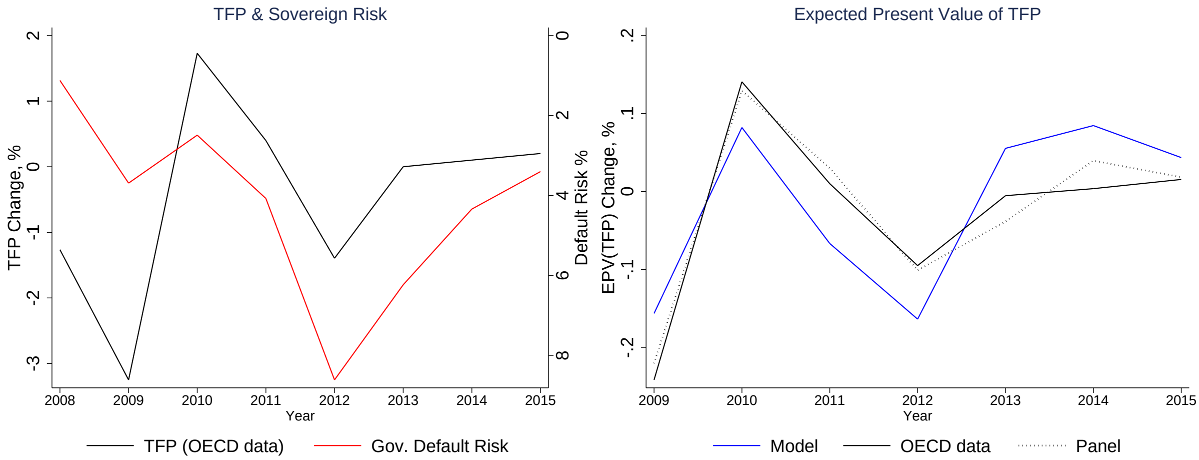
In this appendix, I provide evidence that backs up this modeling strategy. While the goal of this paper is not to formally disentangle the drivers behind changes in sovereign risk and in aggregate TFP, I show that changes in Italy's TFP during the European debt crisis are in fact tightly linked to changes in sovereign risk. Moreover, I show that the model delivers paths of expected aggregate productivity that resemble the ones observed in the data.

Figure C.1 shows different measures of TFP together with the sovereign risk for Italy during the 2008-2015 period. The left-hand side panel of Figure C.1 shows a strong correlation between changes in the Italian TFP and the government's risk-neutral default risk.[70] The right-hand side panel of C.1 shows the *expected present value* (EPV) of future TFP paths. For each year t, this measure is given by:

$$EPV_t(TFP) = \mathbb{E}_t\left[\sum_{l=0}^{\infty}\left(\frac{1}{1+r}\right)^l TFP_{t+l}\right] \tag{C.10}$$

[70] The series for TFP corresponds to the Italian "Multi-factor Productivity" reported by the OECD. It measures the part of GDP growth that cannot be explained by growth in labor and capital inputs.

Figure C.1: TFP and Sovereign Risk



Notes: The left-hand side panel shows changes in Italy's TFP (black line) and the Italian government risk-neutral default probability (red line). The series for TFP corresponds to the Italian "Multi-factor Productivity" reported by the OECD. The default risk is computed from Italian CDS, as explained in Appendix A.9. The right-hand side panel shows the expected present value (EPV) of TFP. The black solid line is based on the "Multi-factor Productivity". The black dotted line is based on a measure of TFP for the panel of Italian firms described in Section 2). The blue solid line shows the model-implied EPV of TFP.

where r is the risk-free rate. The figure compares the EPV for the Italian data (black lines) with the one implied by the model (blue lines), which is a function of the sovereign risk process and the productivity loss upon default (see below for its derivation). While the model does not consider changes in current TFP, the model-implied EPV closely tracks its empirical counterpart. Taken together, these results highlight that the assumed reduced-form productivity loss can approximate reasonably well the (expected) aggregate productivity losses observed in Italy during the period under analysis.

Computing the Expected Present Value (EPV) of TFP

To compute the EPV for the Italian data, I assume the following AR(1) process:

$$log(TFP_{t+1}) = \alpha_0 + \alpha_1 log(TFP_t) + \sigma\epsilon_{t+1} \tag{C.11}$$

and estimate the coefficients $\{\alpha_0, \alpha_1, \sigma\}$ by OLS.[71] Using those estimates, I compute the expected present value of future paths of TFP by simulation. For each year t, I run $J = 10,000$ simulations of length $I = 1,000$ to construct $\{TFP_{j,t+i}\}_{j=1,i=0}^{J,I}$, where the

[71]For the OECD measure of TFP, the estimates are based on data covering the 1985-2015 period. For the panel of non-financial firms, I first estimate an aggregate measure of TFP for the 2000-2015 period and then use those estimates as inputs in equation (C.11). In the latter case, given the small length of the sample period, the results should be considered for illustrational purposes only.

initial value of each simulation, $TFP_{j,t}$, is given by the observed TFP in period t. For each year t, the EPV of TFP is computed as:

$$EPV_t(TFP) = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=0}^{I}\left(\frac{1}{1+r}\right)^{i} TFP_{j,t+i} \tag{C.12}$$

To compute the model-implied expected present value of TFP, I first compute the Italian government quarterly risk-neutral default probability from annual CDS spreads (as explained in Appendix A.9). I then use this series to compute a path for the model's sovereign risk process, $\{s_t\}_{t=2008.q1}^{2015.q4}$.[72] As described in Section 4, this process follows an AR(1) process given by:

$$s_{t+1} = (1-\rho_s)\, s^\star + \rho_s s_t + \sigma_s \epsilon_{t+1}^{s} \tag{C.13}$$

Using equation (C.13) and the calibrated parameters $\{\rho_s, \sigma_s, s^\star\}$, for each period t, I run $J = 10,000$ simulations of length $I = 1,000$ to construct $\{s_{j,t+l}\}_{j=1,i=0}^{J,I}$, where the initial value of each simulation, $s_{j,t}$, is given by the empirical s_t computed above. I use these values to simulate the government's default status $\left\{h_{j,t+l}^{G}\right\}_{j=1,i=0}^{J,I}$, with the initial condition of $h_{j,t}^{G} = 0$ for all j. If the government is not in default, the next-period default status is given by:

$$h_{t+1}^{G} = \begin{cases} 1 & \text{if } \epsilon_{t+1}^{h} < s_t \\ 0 & \text{otherwise} \end{cases}$$

where ϵ_{t+1}^{h} is a standard logistic random variable. If the government is currently in default, the next-period default status is given by:

$$h_{t+1}^{G} = \begin{cases} 0 & \text{if } \epsilon_{t+1}^{e} < \zeta \\ 1 & \text{otherwhise} \end{cases}$$

where ζ is the (model's calibrated) probability of exiting a default and ϵ_{t+1}^{e} is a uniform $[0,1]$ random variable. Based on the default status of the government, the aggregate firms' productivity is given by:

$$\xi_t = \begin{cases} 1 & \text{if } h_t^{G} = 0 \\ \xi_D & \text{if } h_t^{G} = 1 \end{cases}$$

Proceeding in this way, I compute $\{\xi_{j,t+l}\}_{j=1,i=0}^{J,I}$ for each period t. For each year t, the model-implied EPV of TFP is given by:

$$EPV_t(\xi) = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=0}^{I}\left(\frac{1}{1+r}\right)^{i} \xi_{j,t+i} \tag{C.14}$$

[72] For a given default probability d_t, the variable s_t solves: $1 - d_t = \frac{1}{1+exp(s_t)}$.

C.3 Computational Algorithm

The model features several state variables including the firm distribution, an infinite-dimensional object, aggregate uncertainty, and occasionally binding constraints, which makes it challenging to solve. First, I re-express the firms' states in terms of capital, leverage (instead of debt), and productivity. Moreover, instead of keeping track of banks' net worth N (which is unknown at the beginning of each period), I re-express the banks' problem using their deposits (D) as the state variable. After these changes, the states of the model are given by: $\left(k, \tilde{b}, z, s, B, D, h_G, \Omega\right)$, where $\tilde{b}$ refers to firm's leverage and Ω refers to the firm distribution.

To solve for the equilibrium of the model numerically, I follow the bounded rationality approach in Krusell and Smith (1998) and use as state variables a set of statistics that summarize the distribution of firms. From equation (4.15) in the main text, banks' Lagrange multiplier is given by:

$$\mu\left(\boldsymbol{S}\right) = Max\left\{1 - \frac{\tilde{\beta}R_f\left[(1-\psi) + \psi\mathbb{E}\alpha\left(\boldsymbol{S'}\right)\right]}{\kappa\left(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\right)}\eta\,,\,0\right\}$$

From this expression it is clear that, in order to predict current and future loan prices, firms need a perceived policy for firms' loans and defaults to compute the ratio $\tilde{R} \equiv \frac{\eta}{\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega}$ (and its perceived future values). In equilibrium, to guarantee market clearing, firms' perceived value for $\tilde{R}$ must also coincide with the observed value. To avoid inaccuracies that may arise from this perceived law of motion, I instead define $\tilde{R}$ as an auxiliary aggregate variable in the firm's problem. Using $\tilde{R}$ as a state variable has the advantage that the solution guarantees market clearing in each step of the simulation. Moreover, embedded inside $\tilde{R}$, we have relevant information describing firms' distribution across capital and leverage.

Once $\tilde{R}$ is included as a state, other statistics summarizing the firm distribution are only relevant for forecasting $\tilde{R}'$. Let $\tilde{\boldsymbol{S}} \equiv \left(s, B, \tilde{R}, D, h_G, \boldsymbol{m}\right)$ denote the aggregate state, where $\boldsymbol{m}$ denotes other moments describing the firm distribution. The firm's recursive problem can be written as:

$$V\left(k,\tilde{b},z;\tilde{\boldsymbol{S}}\right)=Max_{k',\tilde{b}'}\ d+\beta\mathbb{E}_{\left(z',\tilde{\boldsymbol{S}}'\right)|\left(z,\tilde{\boldsymbol{S}}\right)}\left[max\left\{V\left(k',\tilde{b}',z';\tilde{\boldsymbol{S}}'\right),V^{d}\left(k',e_d'\right)\right\}\right]$$

subject to

$$d=\pi\left(k,\tilde{b},z\right)-I\left(k',k\right)+q\left(.,\tilde{\boldsymbol{S}}\right)\times\left[\tilde{b}'k'-\left(1-m_f\right)\tilde{b}k\right]-\left[\left(1-m_f\right)c_f+m_f\right]bk$$

$$d\geq 0$$

$$\tilde{R}'=H_R\left(\tilde{\boldsymbol{S}}\right)$$

$$D'=H_D\left(\tilde{\boldsymbol{S}}\right)$$

$$\boldsymbol{m}'=H_m\left(\tilde{\boldsymbol{S}}\right)$$

where $H_R(.)$,$H_D(.)$, and $H_m(.)$ denote the perceived law of motions for $\tilde{R}$, D, and for the moments $\boldsymbol{m}$. I assume simple log-linear forecasting rules for both $H_R(.)$ and $H_D(.)$ based on the current aggregate state of the economy. While adding other moments related to the joint distribution of capital and leverage may improve forecastability, I found that adding the first moments of capital and leverage as states does not make significant improvements, while they significantly increase computational times due to the curse of dimensionality.

The algorithm proceeds in three steps. In the first step, I guess a perceived law of motions for $\tilde{R}'$ and D', and solve for the banks' stochastic discount factor (aggregate kernel). In the second step, taking the solution from the first step as given, I solve the firm's problem. In the third step, I simulate the economy and update the perceived law of motions for $\tilde{R}'$ and D'. I iterate on these three steps until convergence on the coefficients of the perceived law of motions.

I approximate all the functions using linear interpolation. The firms' TFP and the aggregate sovereign risk processes are discretized using Tauchen's method. Grids of evenly distributed points are constructed for all the states. I use 20 points for k, 10 points for $\tilde{b}$, 7 points for z, 4 points for s, 3 points for B, 4 points for $\tilde{R}$, and 4 points for D. Taking into account the two possible values for h_G, this implies a total of $537,600$ state-space points.

The routine to solve for the aggregate kernel is as follows:

1. Guess government bond prices $q_B\left(\tilde{\boldsymbol{S}}\right)$ and the banks' marginal valuation $\alpha\left(\tilde{\boldsymbol{S}}\right)$ for all $\tilde{\boldsymbol{S}}$.
2. Using $q_B\left(\tilde{\boldsymbol{S}}\right)$, compute the next-period stock of government debt: $B'\left(\tilde{\boldsymbol{S}}\right)$.
3. Based on the guessed law of motions for $\tilde{R}'$ and D', compute $\alpha\left(\tilde{\boldsymbol{S}}'\right)$ for every possible next-period aggregate state $\tilde{\boldsymbol{S}}'$. Compute $\mathbb{E}\left[\alpha\left(\tilde{\boldsymbol{S}}'\right)\right]$.
4. Using the banks' balance sheet and the perceived law of motions, compute banks' net worth η. Use this value to compute $\mu\left(\tilde{\boldsymbol{S}}\right)$.

5. Compute banks' SDF and update $\alpha\left(\tilde{\boldsymbol{S}}\right)$ and $q_B\left(\tilde{\boldsymbol{S}}\right)$. Continue iterating until convergence of the guesses.

In the second step of the algorithm, taking the banks' stochastic discount factor as given, I solve for the firms' optimal choices following these steps:

1. Guess the value function $V\left(k, \tilde{b}, z; \tilde{\boldsymbol{S}}\right)$ and the pricing kernel $q\left(k, \tilde{b}, z, \tilde{\boldsymbol{S}}\right)$ for each point of the state space and for each possible choice of next-period capital and leverage.
2. Taking the pricing kernel as given, solve the firms' problem and update the value function accordingly.
3. Using the optimal policies computed in step 2, update the pricing function using equation (4.21).
4. Iterate until convergence of both $V(.)$ and $q(.)$.

Going into the specifics of the algorithm, I approximate the pricing schedule on a finer grid of 50 points for both k and $\tilde{b}$. This extra degree of flexibility is helpful because pricing kernels are typically more nonlinear than value functions (given the presence of the default cutoff). As the problem presents several non-convexities, I use a global optimization algorithm to solve for k' and $\tilde{b}'$. In particular, I use 150 and 50 points for the decision variables k' and $\tilde{b}'$, respectively. This step of the algorithm relies on the use of graphics processing units (GPUs) to speed up the computations. The advantage of using GPUs is that I can make use of the hundreds of cores inside a GPU to highly parallelize the previous global solution algorithm (and also to compute prices faster).

The last step of the algorithm consists on simulating the economy in order to update the predicted law of motions. The simulation follows the non-stochastic approach of Young (2010). By not relying on the simulation of individual firms, this approach avoids the sampling error associated with individual firm simulation.[73] This is important in the context of the model given that, due to the firm's default cutoff, small sampling errors may lead to large swings in aggregate default and, therefore, in banks' net worth. In each step of the simulation, I solve for the value of the auxiliary variable $\tilde{R}$ that guarantees market clearing in the loan market. I use a simple bisection algorithm to solve for this variable. I simulate the economy for $T = 5,000$ periods, discard the first $1,000$ periods, and use the simulated objects to run OLS regressions to update the coefficients of the predicted log-linear law of motions for $\tilde{R}'$ and D'. I iterate on this algorithm until convergence on the coefficients of the predicted log-linear law of motions is reached.

[73]For the non-stochastic steady state, I use stochastic simulations to compute the moments described in Table 5.2.