The Asymmetric Pass-Through of Sovereign Risk

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Abstract

This paper studies the role of firm heterogeneity and financial frictions during sovereign debt crises. I consider a heterogeneous-firms model with endogenous default and a financial sector. In the model, a rise in sovereign risk affects firms' incentives to default, increasing corporate risk. Increases in either sovereign or corporate risk hurt banks' lending capacity, affecting firms' borrowing costs and default risk. The model features a doom loop between corporate risk and banks' net worth, which depends on the intensity of the transmission of sovereign risk to the non-financial firms. I use Italian firm-level data to estimate this transmission. I find that sovereign risk significantly increases the default risk of (ex-ante) riskier firms but safer firms are almost unaffected. I use those estimates to discipline the model and find that, through its effect on banks' net worth, corporate risk amplifies the drop in output during a sovereign debt crisis by more than 25%.

Keywords: Corporate risk, sovereign risk, firm heterogeneity, financial frictions.
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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.[1] In this paper, I argue 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 sovereign debt crises are characterized by large and heterogeneous increases in non-financial default risk. 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**.** In this paper, I fill this gap by providing a quantitative model to study the macroeconomic effects of increases in corporate risk around sovereign debt crises.

Disentangling the macroeconomic implications of sovereign and corporate risk is difficult given that they are jointly determined. In this paper, I formulate a heterogeneous-firms model in which corporate risk is endogenously linked to sovereign risk. In the model, exogenous changes in sovereign risk are transmitted to the non-financial firms, increasing their default risk. I use Italian firm-level data to estimate this transmission and use those estimates to discipline the model. Using the calibrated model, I then study how the presence of corporate risk can amplify a sovereign debt crisis. I focus on a particular amplification mechanism, which is the doom loop between corporate risk and banks' balance sheets.

The model features 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 endogenously default on their loans. The government issues transfers to households, collects taxes from firms, and issues long-term bonds. Government bonds are risky because the government can default on these bonds. I assume that sovereign risk is an exogenous process, independent of the fundamentals of the economy. The supply of credit is provided by domestic banks, which are owned by the households. To finance their loans, each banker uses its own net worth and households' deposits. I introduce an agency problem between banks and depositors (as in Gertler and Karadi, 2011) that leads to an endogenous leverage constraint, which in turn limits the banks' ability to supply credit. Under this setup, the supply of credit is a function of changes in both sovereign and corporate risk.

[1]See, for instance, Bottero et al., 2020, Arellano et al., 2019, Buera and Karmakar, 2018, Bocola, 2016, and Gennaioli et al., 2014.

There are two channels through which sovereign risk affects corporate risk. First, increases in sovereign risk weaken banks' balance sheets, which reduces the supply of credit. A lower supply of credit makes it harder for firms to roll over their existing loans, which increases their likelihood to default (i.e., corporate risk). Second, a sovereign default triggers exogenous productivity losses. Even if the sovereign default is not realized, an increase in sovereign risk decreases firms' expected future productivity, which leads to higher corporate risk. In addition to these channels, the model features a two-way feedback loop (or doom loop) between corporate risk and banks' net worth. This is because increases in corporate risk also deteriorate banks' balance sheets, affecting the credit supply and firms' incentives to default. The strength of this doom loop depends on the intensity of the transmission of sovereign risk to corporate risk. Quantifying this transmission is thus crucial to asses the relative importance of the doom loop. To this end, I use Italian firm-level data to estimate the (combined) transmission of sovereign to corporate risk and use those estimates to discipline the model.

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 focus on high-frequency market reactions around a set of specific events. In particular, I employ an instrument constructed by Bahaj (2020) that isolates changes in sovereign risk that are orthogonal to the economy's fundamentals. The analysis relies on high-frequency tick-by-tick data and a narrative analysis based on a set of "foreign news events" during the European debt crisis. I focus on a set of news events from Greece and Portugal and construct sovereign risk shocks based on the change in Italian sovereign spreads in a narrow 40-minute window around each event. The type of identification is similar to the literature on monetary policy shocks (see, for instance, Gorodnichenko and Weber, 2016 and Gertler and Karadi, 2015).

To quantify corporate risk, I construct a high-frequency measure of default risk for a panel of publicly traded non-financial Italian firms, based on Merton's (1974) distance-to-default framework. I use a sample of German firms to control for potential common factors such as a change in risk aversion in the market price of risk. In the absence of cross-country market segmentation, a change in the market price of risk should have similar effects across European firms with similar risk profiles. Based on this observation, I create pairs made up of one Italian and one German firm with similar pre-crisis risk profiles and study the differential response of the Italian firm to a sovereign risk shock.

I show that sovereign risk leads to a significant increase in the default probability of non-financial firms. A one-standard deviation increase in the sovereign risk shock leads to a 0.52 percentage points increase in corporate risk. The effects are quite persistent, lasting about five quarters. The estimates account for about 50% of the total increase in Italian corporate risk. Moreover, the results highlight the presence of an asymmetric pass-through of sovereign risk. While, on aggregate, sovereign risk is quickly transmitted to the corporate sector, there is a large heterogeneity across firms behind this transmission. Firms with a lower (ex-ante) default probability, firms with smaller leverage, and firms with a larger share of liquid assets are significantly less affected by the sovereign risk shock.

Although I do not formally disentangle the channels behind the transmission of sovereign risk to the non-financial firms, I present evidence that highlights the role of banks. By exploiting within-region banks' heterogeneity in their exposure to sovereign risk, I show that even after controlling for many bank characteristics that capture the pre-crisis credit quality of their loan portfolios, a larger exposure to sovereign risk is associated with a larger increase in corporate risk (as measured by corporate non-performing loans, NPLs).

I use the empirical estimates to calibrate the model and use it to study the aggregate implications of this asymmetric pass-through of sovereign risk. The quantitative 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 algorithm and 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.

The calibrated model is able to reproduce the aggregate transmission of sovereign risk as well as the asymmetric response of corporate risk across firms with different levels of risk. By means of different counterfactuals, I show that during a sovereign debt crisis: (i) corporate risk contributes to almost half of the drop in banks' net worth; and (ii) the doom loop between corporate risk and banks' balance sheets amplifies the drop in output by more than 25%.

Lastly, I exploit the heterogeneity of firms in the model 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 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 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.

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. It is also connected to a broader literature on the firm-level responses to aggregate shocks and on the doom loops between corporate risk and the financial sector.

The paper is closely related to the quantitative literature on the transmission of sovereign risk to the real economy through the financial sector (Ari, 2019, Perez, 2018, Sosa-Padilla, 2018, Bocola, 2016, and Gennaioli et al., 2014). The closest study is Bocola (2016), who considers a model in which news about a sovereign default decrease banks' net worth, limiting their ability to provide credit and affecting the real economy. The 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. Hur et al. (2021), Arellano et al. (2019), Farhi and Tirole (2018), and Acharya et al. (2014) analyze different feedback mechanisms to 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 also emphasize the role of firm heterogeneity behind their feedback mechanism. Hur et al. (2021), 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 relates to an empirical literature that quantifies the transmission of sovereign risk to both corporate and financial risk (Augustin et al., 2018, Almeida et al., 2017, Adelino and Ferreira, 2016, and Acharya et al., 2014).[2] It also connects to a strand of the literature that uses a narrative approach based on news events to capture exogenous variation in sovereign risk (Bahaj, 2020, Hébert and Schreger, 2017, Brutti and Sauré, 2015, and Beetsma et al., 2013). My contribution to this strand of the literature is to describe and quantify an important asymmetric transmission of sovereign risk to non-financial firms and analyze its macroeconomic implications.

The paper also connects to the empirical literature on the determinants of 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. I contribute to this strand of the literature by 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.[3]

[2] 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. Also using CDS data, Acharya et al. (2014) measure the spillover effects from sovereign risk into financial firms around Lehman's bankruptcy. The use of CDS implies that the distribution of firms is tilted toward the largest European firms (even from the subsample of publicly traded firms). An advantage of my analysis is that, by using Merton's (1974) distance to default as a measure of corporate risk, the sample also includes smaller publicly traded firms.

[3] The closest paper in this regard is Farinha et al. (2019), which quantifies the likelihood of a corporate default for firms that are linked to banks with different degrees of sovereign exposure.

More generally, the paper relates to a broader literature on the firm-level responses to aggregate shocks. Kroen et al. (2021), Ottonello and Winberry (2020), Cloyne et al. (2019), Jeenas (2019), and Gertler and Gilchrist (1994) are examples of papers studying the heterogeneous reactions across firms to monetary policy shocks, based on a firm's market concentration, default risk, age, and liquidity. I complement these studies by analyzing the heterogeneity across non-financial firms to a sovereign risk shock.

Lastly, the paper is linked to a DSGE literature on the feedback loops between financial and non-financial sectors. Elenev et al. (2020) and Ferrante (2019) are recent examples of general equilibrium models with financial intermediaries and non-financial default risk. These studies build on canonical models with financial frictions (as in Brunnermeier and Sannikov, 2014, He and Krishnamurthy, 2013, and Gertler and Karadi, 2011) but consider the possibility of corporate defaults, which in turn affects banks' balance sheets. My contribution to this literature is to highlight the role of heterogeneity across non-financial firms in this type of feedback loop. The analysis highlights that (ex-ante) riskier firms are mainly the ones affecting banks' valuation during periods of distress and discusses the effectiveness of policies that directly target these firms.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 presents the empirical analysis on the transmission of sovereign to corporate risk and the role of banks in that transmission. Section 4 presents the quantitative analysis. Section 5 concludes.

2 The Model

I consider a model with incomplete markets and three sectors: a corporate sector formed by heterogeneous firms (entrepreneurs), 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 banks, 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. They are subject to an agency problem that generates an endogenous leverage constraint, which limits their ability to provide credit.

2.1 Firms

There is a unit mass of heterogeneous firms (entrepreneurs) 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. The latter follows a continuous Markov process

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

I assume that firms' aggregate productivity ξ depends on the default status of the government. This variable captures productivity losses faced by firms in the event of a sovereign default and it is given by

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

For a given choice of labor l, profits are given by: $\pi(l) = (1-\tau)\left[y(l) - w \times l\right]$, where τ is the proportional tax on firms' 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

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

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

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

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 convex adjustment costs. 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 $I\left(k',k\right) = \Delta\left(k',k\right) + \Psi\left(k',k\right)$, where $\Psi\left(k',k\right) \equiv \frac{\psi_k}{2}\left(\frac{\Delta(k',k)}{k}\right)^2 k$ is a standard convex adjustment cost. Purchases of capital can be financed with internal resources (retained dividends), by issuing debt in the form of long-term loans granted by the domestic banks (b), or by issuing new funds (e). As in Gilchrist et al. (2014), Cooley and Quadrini (2001), and Gomes (2001), I assume a constant marginal cost of issuing new funds, given by $\bar{\varphi}(e) = e + \varphi max\left\{e, 0\right\}$, where φ measures the degree of frictions in the stock market. 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.[4] Debt issuance is subject to adjustment costs given by $\psi_b(b', b)$. 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

$$R(k, b, z) = \lambda \times \frac{\pi(k, b, z) + (1-\delta)k}{b}. \tag{4.5}$$

The firm's state space can be written as the n-tuple $(k, b, z; \boldsymbol{S})$, where $\boldsymbol{S}$ denotes the aggregate state, which 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'). Firms' dividends are given by

$$d = \pi(k, b, z) - I(k', k) + q(k', b', z; \boldsymbol{S}) \times [b' - (1-m_f)b] - [(1-m_f)c_f + m]\, b, \tag{4.6}$$

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. I assume that firms are subject to a no negative dividend constraint (i.e., $d \geq 0$).[5]

Firms have an outside option available, which depends on the firms' size. The recursive problem of an incumbent firm is given by:

$$V^r(k, b, z; \boldsymbol{S}) = Max_{k',b',e} \ \ (d - \bar{\varphi}(e)) + \beta \mathbb{E}_{\left(z', \boldsymbol{S}', \nu_d'\right)|(z, \boldsymbol{S})} \left[max\left\{V^r(k', b', z'; \boldsymbol{S}'), V^d(\nu_d')\right\}\right]$$

subject to

$$\begin{aligned}
& d = \pi(k, b, z) - I(k', k) + q(., \boldsymbol{S}) \times [b' - (1-m_f)b] - [(1-m_f)c_f + m_f]\, b + \\
& \quad - \psi_b(b', b) + e \\
& d \geq 0 \\
& \boldsymbol{S}' = H(\boldsymbol{S}),
\end{aligned} \tag{4.7}$$

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 is given by $V^d(\nu_d) \equiv \nu_d$, where $\nu_d \sim N(0, \sigma_d)$. At the beginning of each period, for a given a realization for ν_d, the firm's default policy is given by[6]

$$\tilde{h}(k, b, z; \boldsymbol{S}, \nu_d) = \begin{cases} 1 & \text{if } V^r(k, b, z; \boldsymbol{S}) < V^d(\nu_d) \\ 0 & \text{otherwise.} \end{cases}$$

[4]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.

[5]It is easy to show that the firm issues new funds if and only if the dividend constraint is binding. See Gilchrist et al., 2014.

[6]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.

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

$$h(k,b,z;\boldsymbol{S}) = 1 - \Phi\left(\frac{V^r(k,b,z;\boldsymbol{S})}{\sigma_d}\right),$$

where Φ is the cdf of a normal distribution. 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.[7]

Let $\mathbb{R}_f(.,\boldsymbol{S}') \equiv \mathbb{R}_f(k',b',z';\boldsymbol{S}')$ denote the next-period gross repayment per unit of loan for each firm. It is given by

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

where $M_f(k,b,z;\boldsymbol{S}) \equiv (1-m_f)(c_f + q(k',b',z;\boldsymbol{S})) + m_f$, and $k' \equiv k'(k,b,z;\boldsymbol{S})$ and $b' \equiv b'(k,b,z;\boldsymbol{S})$ denote a firm's optimal policy functions. The pricing kernel is given by (see Appendix C.1 for the derivation)

$$q(k',b',z;\boldsymbol{S}) = \mathbb{E}_{(z',\boldsymbol{S}')|(z,\boldsymbol{S})}\left[\Xi(\boldsymbol{S}',\boldsymbol{S}) \times \mathbb{R}_f(k',b',z';\boldsymbol{S}')\right]. \tag{4.8}$$

From Equation (4.8), it is then clear that the firm's borrowing costs depend on its own probability of default and recovery value as well as on the discount factor of the domestic banks.

2.2 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 $w \geq 0$. I assume constant wages and thus the firms' aggregate demand for labor, $\int l(.,\boldsymbol{S})d\Omega$, pins down the equilibrium level for l.[8] For 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

[7] 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).

[8] 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, for tractability, I assume that wages cannot adjust to clear the market.

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

$$\begin{aligned}
& W_h(x,\boldsymbol{S}) = Max_{c,x'}\ c + \tilde{\beta} W_h(x',\boldsymbol{S'}) \\
& \text{subject to} \\
& \qquad c + x'\frac{1}{R_f(\boldsymbol{S})} = wl(\boldsymbol{S}) + x + \Pi(\boldsymbol{S}) + T(\boldsymbol{S}) \\
& \qquad c \geq 0,
\end{aligned} \tag{4.9}$$

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.[9]

2.3 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:

$$\begin{aligned}
PS(\boldsymbol{S}) &\equiv \tau \int \pi(k,b,z;\boldsymbol{S})d\Omega - T(\boldsymbol{S}) \\
&= f_B(B),
\end{aligned} \tag{4.10}$$

where $PS(\boldsymbol{S})$ denotes the government's primary surplus and B denotes the stock of government bonds outstanding. Equation (4.10) 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, since 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.

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

$$q_B(\boldsymbol{S}) \times [B' - (1-m_G)B] + PS(\boldsymbol{S}) = [(1-m_G)c_G + m_G] \times B, \tag{4.11}$$

[9] For the parametrization described in Section 4, this constraint never binds, which implies a constant risk-free interest rate given by $R_f(\boldsymbol{S}) = R_f = 1/\tilde{\beta}$.

where $q_B(\boldsymbol{S})$ is the price of one unit of government debt. In the event of default, the government writes off a share Δ_d of its stock of debt. While in default, it cannot issue new debt, nor it has to pay debt services.[10] Moreover, at the beginning of each period, the government exits default with probability ζ. Assuming that the government is not in default, the government's gross repayment per unit of debt is given by

$$\mathbb{R}_G(\boldsymbol{S}) \equiv [1 - h_G(\boldsymbol{S})] M_G(\boldsymbol{S}) + h_G(\boldsymbol{S}) q_B(\boldsymbol{S}) \Delta_d,$$

where $M_G(\boldsymbol{S}) \equiv (1 - m_G)(c_G + q_B(\boldsymbol{S})) + m_G$. The next-period default status is[11]

$$h'_G = \begin{cases} 1 & \text{if } \epsilon'_h < s \\ 0 & \text{otherwise,} \end{cases} \tag{4.12}$$

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 an AR(1) process given by[12]

$$s' = (1 - \rho_s) s^\star + \rho_s s + \sigma_s \epsilon'_s \, ; \; \epsilon'_s \underset{iid}{\sim} N(0, 1) \, . \tag{4.13}$$

The government's pricing kernel is given by

$$q_B(\boldsymbol{S}) = \mathbb{E}_{\boldsymbol{S'}|\boldsymbol{S}} \left[\Xi(\boldsymbol{S'}, \boldsymbol{S}) \times \mathbb{R}_G(\boldsymbol{S'}) \right], \tag{4.14}$$

where $M_G(\boldsymbol{S'}) \equiv (1 - m_G)(c_G + q_B(\boldsymbol{S'})) + m_G$, and $B' = B'(\boldsymbol{S})$ denotes the government's current choice of debt.

2.4 Bankers

Let η denote a 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. A bank's exit is stochastic, occurring with an exogenous probability $(1 - \psi)$. A banker that exits becomes a worker and is replaced by

[10] 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.

[11] If the government is currently in default, the gross repayment per unit of debt is $\mathbb{R}_G(\boldsymbol{S}) \equiv q_B(\boldsymbol{S})$. Its 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.

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

a worker from his household.[13] In this sense, the share of types within each household is constant over time. Taking prices as given, the objective of a banker 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:

$$\kappa\bigg(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\bigg) \leq W\left(\eta,\boldsymbol{S}\right), \tag{4.15}$$

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

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

subject to

$$\begin{aligned}
&\frac{1}{R_f}x' + \eta = \int q\left(.,\boldsymbol{S}\right)b'(.,\boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B' \\
&\eta' = -x' + \int \mathbb{R}_f(.,\boldsymbol{S}')b'(.,\boldsymbol{S})d\Omega + \mathbb{R}_G(\boldsymbol{S}')B' \\
&\kappa\bigg(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\bigg) \leq W\left(\eta,\boldsymbol{S}\right) \qquad (4.16)\\
&\boldsymbol{S}' = H\left(\boldsymbol{S}\right).
\end{aligned}$$

The first restriction represents the balance sheet of the bank. The second restriction is the law of motion for a 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, $\mathbb{R}_G(\boldsymbol{S}')$ and $\mathbb{R}_f(.,\boldsymbol{S}')$. From these expressions, it is then clear that banks' net worth is a function of both sovereign and corporate risk.

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

$$W(\eta,\boldsymbol{S}) = \alpha\left(\boldsymbol{S}\right)\times\eta, \tag{4.17}$$

where

$$\alpha\left(\boldsymbol{S}\right) = \tilde{\beta}R_f\frac{\left[(1-\psi)+\psi\mathbb{E}\alpha\left(\boldsymbol{S}'\right)\right]}{1-\mu(\boldsymbol{S})} \tag{4.18}$$

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

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

$$\mu\left(\boldsymbol{S}\right) = Max\left\{1 - \frac{\tilde{\beta}R_f\left[(1-\psi)+\psi\mathbb{E}\alpha\left(\boldsymbol{S'}\right)\right]}{\kappa\Big(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_B(\boldsymbol{S})B'\Big)}\eta\,,\,0\right\}. \tag{4.19}$$

The linearity of the value function implies that the heterogeneity in banks' 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. 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 depends not only on whether banks' leverage constraint is currently binding or not (i.e., $\mu\left(\boldsymbol{S}\right) \geq 0$) but also on next-period's aggregate state $\boldsymbol{S'}$. Changes in either sovereign or corporate risk, even when they do not lead to a binding leverage constraint, may still affect the banks' current SDF, since they affect the likelihood that the constraint may bind in the future.

2.5 Definition of 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 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 firms', banks' and households' 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.

2.6 Sources of Transmission and Next Steps

For tractability, the model assumes that the sovereign risk process is exogenous and independent of the economy's fundamentals. An obvious limitation of this modeling strategy is that it is silent on the feedback between sovereign and corporate risk.[14] On the other hand, this modeling strategy has the advantage that the sovereign risk process of Equation (4.13), together with the reduced-form productivity loss of Equation (4.3), are flexible enough to match the observed increase in Italian sovereign risk as well as the transmission of sovereign to corporate risk.

There are two channels in the model through which sovereign risk affects corporate risk. The first channel is endogenous and operates through the domestic banks. An increase in sovereign risk reduces the value of government debt, which decreases banks' net worth, η. A drop in η may cause banks' incentive constraint to bind, which, from Equations (4.19) and (4.20), decreases banks' stochastic discount factor and thus lowers the price of firms' loans (i.e., it rises corporate spreads). In this context, firms' borrowing costs increase, which affects their incentives to default and increases corporate risk.

The second channel is exogenous and works through firms' productivity. Equation (4.3) assumes an exogenous efficiency cost for the corporate sector in the event of a sovereign default ($\xi_D < 1$). 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.[15] Even if the sovereign default is not realized, an increase in sovereign risk decreases firms' expected future productivity, which in turns leads to higher corporate risk.[16]

On top of these two channels, the model features a two-way feedback loop (or doom loop) between corporate risk and banks' net worth. This is because increases in corporate risk also deteriorate banks' balance sheets, affecting the credit supply and firms' incentives to default.

For illustration purposes and to better understand the mechanisms at play, suppose that we can summarize the model in the following non-linear system of equations:

$$\begin{aligned} \eta &= G\left(SR, CR\right) \\ CR &= F\left(SR, \eta\right), \end{aligned}$$

where we are implicitly using the fact that sovereign risk is exogenous. By totally differentiating these two expressions, we get that

$$\begin{aligned} \Delta\eta &= G'_{SR}\Delta SR + G'_{CR}\Delta CR \\ \Delta CR &= F'_{SR}\Delta SR + F'_{\eta}\Delta\eta, \end{aligned}$$

[14] Arellano et al. (2019) provide a model that analyzes the feedback between sovereign risk and the economy's fundamentals.

[15] 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.

[16] 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.

Combining terms, we have that

$$\Delta CR = \frac{1}{1 - F'_\eta G'_{CR}} \left(F'_\eta G'_{SR} + F'_{SR} \right) \times \Delta SR$$
$$\equiv \alpha_1 \times \Delta SR. \tag{4.21}$$

The $F'_\eta G'_{SR}$ term captures the endogenous transmission of sovereign risk through the domestic banks. The term F'_{SR}, on the other hand, refers to the exogenous transmission of risk (through lower firms' productivity). Lastly, the term $\frac{1}{1-F'_\eta G'_{CR}}$ captures the amplification mechanism that arises due to the feedback between banks' exposure to corporate risk, the supply of credit, and firms' incentives to default.

In the next section, I use Italian data to estimate the transmission of sovereign risk to corporate risk (i.e., the α_1 parameter). In the quantitative analysis of Section 4, I use those estimates to discipline the model. Using the calibrated version of the model, I disentangle the different channels behind this transmission. The ultimate goal is to quantify the relative importance of the amplification mechanism given by $\frac{1}{1-F'_\eta G'_{CR}}$ and the role of firm heterogeneity behind this amplification.

3 Empirical Analysis: Heterogeneous Transmission of Sovereign Risk

In this section, I quantify the transmission from sovereign to corporate risk. The goal of this section is twofold. First, I estimate the aggregate transmission of sovereign risk to corporate risk (i.e., the α_1 parameter of Equation 4.21). Second, I describe a large heterogeneity across the non-financial firms behind this transmission. Third, I highlight the role of banks in the transmission.

3.1 Data Sources and Construction of Corporate Risk

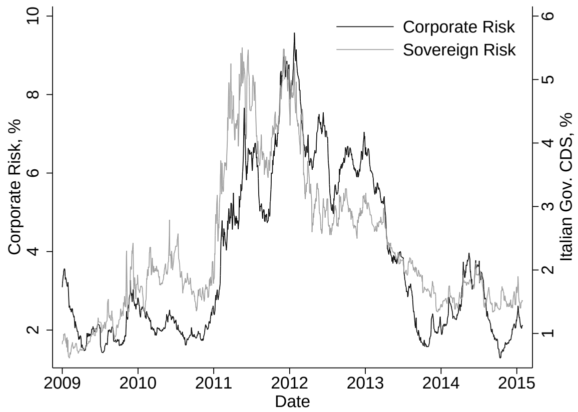
The analysis in this section uses high-frequency Italian firm-level data. To quantify corporate risk, I retrieve financial data for about 200 publicly traded non-financial Italian firms that were active (at least) during the 2007-2013 period. Data was retrieved from Bloomberg and Compustat. From Bloomberg, I retrieve daily information of stock prices and shares outstanding for each firm. I use Compustat to get firms' quarterly balance-sheet data. The main variables included in the analysis are: total assets, liabilities (short- and long-term), liquid assets, and sales.

To measure non-financial firms' default risk, I employ the distance-to-default framework developed by Merton (1974).[17] The key insight of this approach is to view the equity

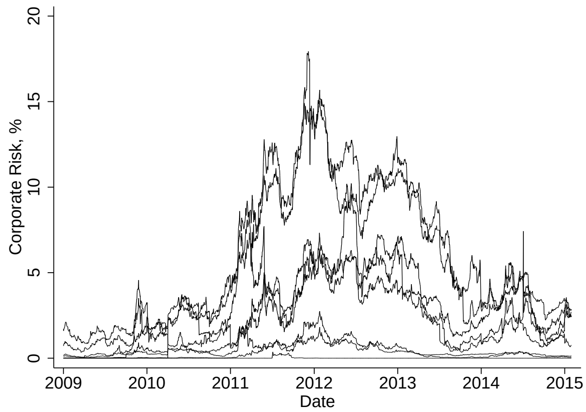
[17]The distance-to-default framework has been used extensively in the literature. See, for instance, Bharath and Shumway (2008), Gilchrist and Zakrajšek (2012), and Ottonello and Winberry (2020).

Figure 3.1: Italian Sovereign and Corporate Risk

(a) Aggregate Transmission



(b) Heterogeneous Effects



Notes: The left panel shows measures for Italian sovereign and corporate risk. The gray line depicts the 10-year Italian government credit default swaps (CDS). The black line shows the unweighted average of the non-financial credit risk measure based on Merton's distance-to-default framework. The right panel shows the evolution of Italian corporate credit risk for different percentiles of the firms' distribution. Firms are sorted into 10 different bins based on their default risk in 2009. Results for the first 8 bins (safer firms) are included in the graph.

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, 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 bond spreads or CDS is that the latter are only available for the largest firms, even from the pool of publicly traded firms (Subrahmanyam et al., 2014). In the Merton's model, a firm defaults whenever $ln(V_{j,t}/D_{j,t}) < 0$, where $V_{j,t}$ is the (unobserved) value of firm j and $D_{j,t}$ is the face value of its debt. The distance-to-default measure ($dd_{j,t}$) can be interpreted as the number of standard deviation that the $ln(V_{j,t}/D_{j,t})$ 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 $CR_{j,t} \equiv \Phi(-dd_{j,t})$, where $\Phi(.)$ is the cdf of the standard normal distribution (see Appendix A.1).

The left panel of Figure 3.1 plots an aggregate measure of Italian corporate risk together with the Italian government CDS. 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 late 2012, both measures increased sharply. The right panel shows the evolution of Italian corporate risk for firms with different levels of risk. As the crisis evolves, there is not only an increase in the median default risk, but also in its dispersion. In particular, riskier firms (i.e., those with an ex-ante higher default probability) experience a larger increase in their default probability during the crisis period.

3.2 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.

To estimate this transmission, I focus on high-frequency market reactions around a set of specific events. To this end, I employ a high-frequency instrument constructed by Bahaj (2020) that isolates exogenous changes in sovereign risk. Bahaj's analysis relies on tick-by-tick data and a set of "foreign news events" during the European debt crisis. To compile a set of events, he uses the news source EuroIntelligence for the July 2009 - March 2013 period. To be included in the narrative, the news must satisfy the following criteria. First, it must relate to a single crisis-hit country (Greece, Cyprus, Portugal, Ireland, Italy or Spain) and it cannot affect the Euro area as a whole. Second, it must be timeable. Using Bloomberg newswire, Bahaj is able to precisely time (at the minute) when these events happened and creates narrow windows around each news event. Based on this set of news, he then construct a measure of sovereign risk shocks as the change in the sovereign bond spreads of country X in a narrow 40-minute window around the news events from country Y.[18]

To avoid potential endogeneity issues, the following news are excluded from the analysis: (i) foreign interventions (for instance, ECB or IMF announcement of a bailout program); and (ii) events related to the sovereign bond market itself (for instance, credit rating downgrades). First, international policymakers may be internalizing the effects on the entire European union when making their decisions. This would imply, for instance, that an ECB announcement regarding a Greek bailout may be motivated by the fundamentals of the Italian economy, invalidating the instrument. Second, rating announcements are also omitted because credit rating agencies often downgrade several sovereigns and financial institutions at the same time. Lastly, foreign events that overlap with a local event are also excluded.

For the analysis of this section, I focus on the set of news from Greece and Portugal listed in Bahaj (2020). The sovereign risk shock, ξ_t, is given by the change in the 10-year Italian government credit spread (relative to the German bund) in a narrow 40-minute window around each foreign news event. Table 3.1 provides some summary statistics of the sovereign risk shock, aggregated at a daily frequency.[19] Figure 3.2 compares the (cumulative) evolution of the shocks to the observed Italian sovereign risk (based on the 10-year CDS spread). Overall, the shocks track the observed evolution of Italian sovereign risk relatively well.

[18] The majority of the news in the dataset includes announcements or statements to the press from an official (foreign) government source. Local news are excluded from the analysis because they may be informative about the fundamentals of the local economy. For instance, the market reaction to a local announcement of an austerity package may well reflect the market's response to a fiscal news shock. For the same reason, Euro-area news are also excluded from the analysis.

[19] Appendix A.3 shows the same statistics but aggregated at a quarterly frequency.

Table 3.1: Italian Reaction to Foreign News Events

	Greece	Portugal	G&P
Number of Events (days)	63	33	94
Mean Market Reaction (bps)	1.91	-0.05	1.26
Std. Dev. Market Reaction (bps)	8.64	2.90	7.33
Min Market Reaction (bps)	-18.60	-6.55	-18.60
Max Market Reaction (bps)	44.40	9.65	44.40

Notes: The table reports the change in Italian sovereign spreads in 40-minute window around news events from Greece and Portugal. Market reactions are aggregated at the daily frequency. Events are based on Bahaj (2020). Italian spreads are computed as the difference between the 10-year Italian government bond yield versus the 10-year German government bond yield. Sample period: 2009-2013.

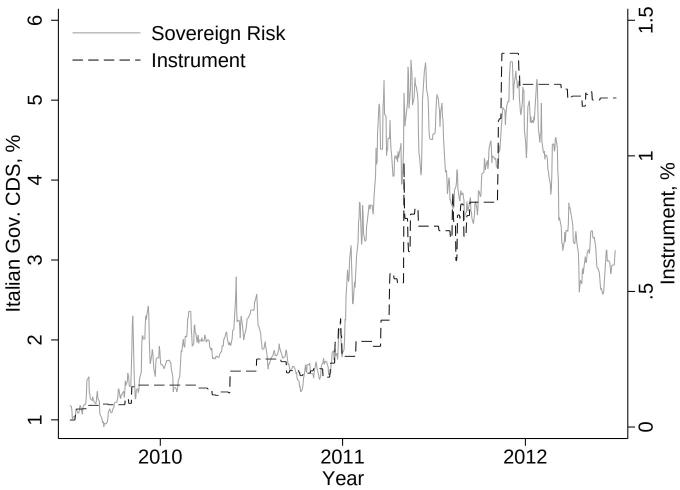
There are four underlying assumptions behind the identification strategy. The first one is that Italian firms are not directly affected by the foreign news events apart from the effect through the change in Italian sovereign risk. In other words, these high-frequency market reactions capture plausibly exogenous shocks to the Italian government default probability and, therefore, allow to identify the causal link of sovereign risk on corporate risk. This is a reasonable assumption given the weak trade and financial linkages between Italy and these two other countries.[20] Bahaj (2020) provides a formal analysis showing that countries inter-linkages have no explanatory power over relative market reactions to the news events.

Second, the foreign news from Greece and Portugal affect Italian sovereign risk. This in fact seems to be the case as shown in Figure 3.2. While the analysis is silent on the sources of cross-country transmission of risk, it can be driven by self-fulfilling beliefs (Cole and Kehoe, 2000), a wake-up-call (Beirne and Fratzscher (2013) and Giordano et al. (2013)), common lenders (Arellano et al. (2018)), fear of euro exit, and redenomination risk (Krishnamurthy et al., 2018).

The third assumption is that the foreign news events have no effect on common factors behind the pricing of sovereign and corporate risk. An important concern is that these news may have triggered a change in risk aversion or in the market price of risk across Europe. In the absence of cross-country market segmentation, however, a change in the market price of risk should have similar effects across European firms with similar risk profiles. Motivated by this observation, I employ a sample of non-financial German firms to control for changes in common factors.

[20]For instance, (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 represents 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. Tables A.1-A.3 in Appendix A.2 provide the supporting evidence.

Figure 3.2: Italian Sovereign and Corporate Risk



Notes: The figure compares the sovereign risk shock constructed by Bahaj (2020) (dotted black line) with a measure of Italian sovereign risk (solid gray line). The shock is based on high-frequency market reactions to news from Greece and Portugal. The measure of sovereign risk is based on the 10-year Italian government credit default swaps (CDS). Variables are reported at a daily frequency.

3.3 Framework and Results

We are interested in estimating (i) the aggregate transmission of sovereign risk to corporate risk, and (ii) the differential transmission across firms with different levels of risk. In order to account for this transmission at different horizons h, I consider the following Jorda(2005)-style local projection:

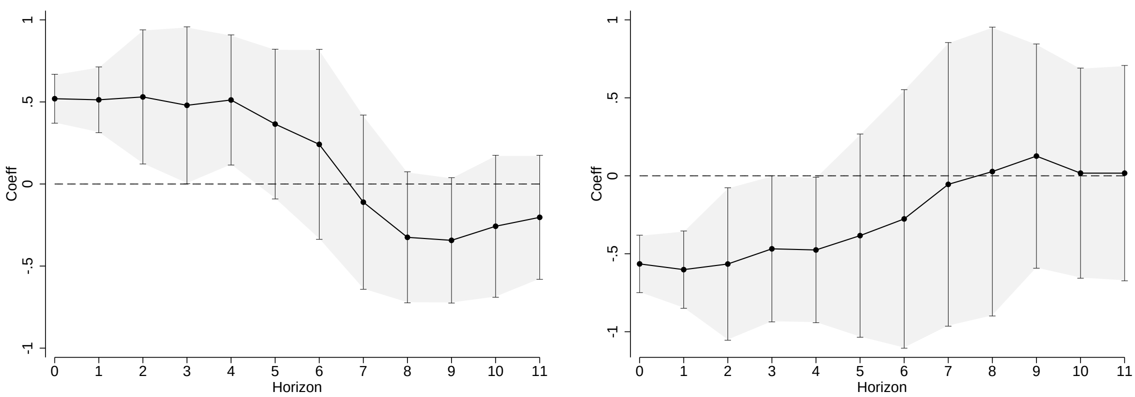
$$\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times a_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}, \tag{3.1}$$

where $\Delta CR_{j,t+h}$ is the cumulative change in corporate risk of firm j at horizon h, ξ_t is the sovereign risk shock, $a_{j,t-1}$ is the firms' financial position, $Z_{j,t-1}$ is a vector of firm-level controls, and γ_j are firm fixed effects. The vector $Z_{j,t-1}$ includes the level of $dd_{j,t-1}$, and 1-period lags of total assets (in logs), leverage, share of liquid assets over current assets, and sales over assets. I normalize ξ_t by its standard deviation and $a_{j,t-1}$ is demeaned and divided by its standard deviation. Under this specification, the parameter α_{1h} captures the cumulative aggregate change of corporate risk at time $t+h$ to a 1-standard deviation sovereign risk shock at time t. The parameter α_{2h} measures how the response of corporate risk depends on the firms' financial position at the moment of the shock. I use three different measures of a firm's financial position: the distance to default ($dd_{j,t-1}$), leverage ($lev_{j,t-1}$), and the share of liquid assets ($liq_{j,t-1}$).

Figure 3.3 presents the results when using the distance to default, $dd_{j,t-1}$, as a firm's financial position. The left panel shows the estimates for α_{1h} coefficients. On impact, a 1-standard deviation increase in the sovereign risk shock leads to an additional 0.52pp increase in the aggregate corporate risk. The effects are quite persistent, lasting about

Figure 3.3: Asymmetric Transmission of Sovereign Risk; Dynamics

(a) α_{1h} Coefficients (b) α_{2h} Coefficients



Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. Panel (a) reports the α_{1h} coefficients over quarters h. Panel (b) shows the α_{2h} coefficients. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

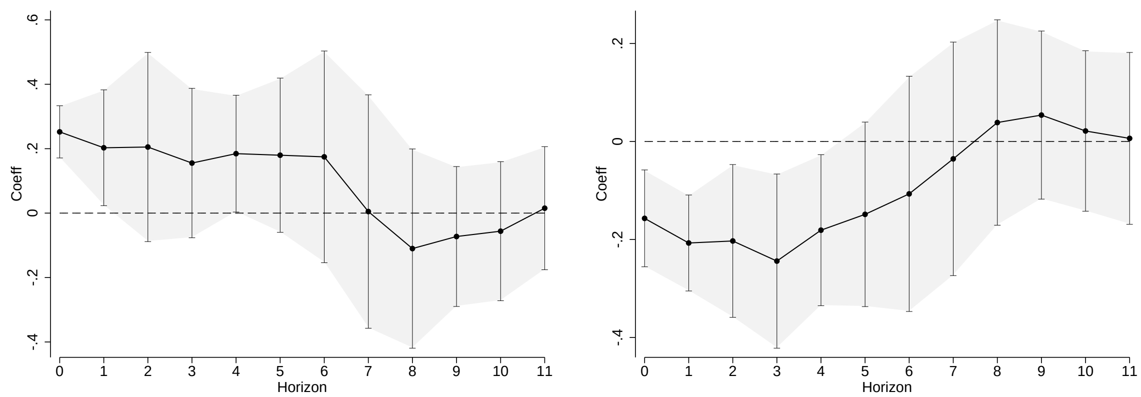
five quarters. The right panel shows the estimates for the α_{2h} coefficients. Firms whose distance to default is one standard deviation above the average (i.e., safer firms) are significantly less affected by sovereign risk. In particular, notice that $\alpha_{1,h} + \alpha_{2,h}$ is close to zero, indicating that the corporate risk of safer firms is almost unaffected by changes in sovereign risk. Figure 3.4 complements the analysis by showing how firms with different levels of leverage ($lev_{j,t-1}$) and liquid assets ($liq_{j,t-1}$) are affected by changes in sovereign risk. Firms with higher leverage experience a larger increase in corporate risk while those with larger cash holdings are significantly less affected. In Appendix A.3, I show that all these results are robust to the inclusion of time fixed effects.

Taken together, these results highlight the presence of an asymmetric pass-through of sovereign risk. While, on aggregate, sovereign risk is quickly transmitted to the corporate sector, there is a large heterogeneity across firms behind this transmission. Safer firms, firms with smaller leverage, or firms with a larger share of liquid assets, are significantly less affected. A simple back-of-the-envelope calculation suggests that these results are economically important, explaining almost 50% of the increase in Italian corporate risk.[21] In Appendix A.3, I show that this asymmetric transmission of sovereign risk has important real consequences. In particular, riskier firms decrease their investment significantly more than safer firms.

[21]The total change in Italian corporate risk during the crisis period was about 600bps. Given that the total cumulative change in the ξ_t shock was about 120bps and its standard deviation (at the quarterly frequency) was about 14bps, then sovereign risk can account for 400bps of the increase. After controlling for German firms (see Figure 3.5), sovereign risk can still account for around 300bps of the increase.

Figure 3.4: Asymmetric Transmission of Sovereign Risk; Dynamics

(a) Leverage (b) Liquid Assets



Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times a_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. Panel (a) reports the α_{2h} coefficients when using $a_{j,t-1} = lev_{j,t-1}$. Panel (b) shows the α_{2h} coefficients for the case in which $a_{j,t-1} = liq_{j,t-1}$. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

Role of Common Factors

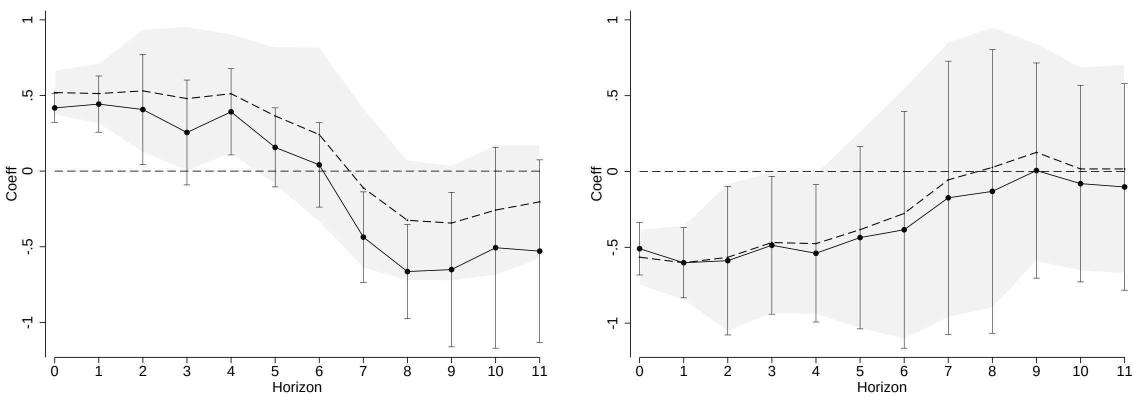
An important concern behind the previous analysis is that the foreign news may have triggered a change in risk aversion or in the market price of risk across Europe. If that were the case, the previous estimates would be biased, because they would be capturing the co-movement between sovereign and corporate risk due to a common shock. In the absence of cross-country market segmentation, however, a change in the market price of risk should have similar effects across European firms with similar risk profiles. Based on this observation, I employ a sample of non-financial German firms to control for changes in common factors. In particular, I create pairs made up of one Italian and one German firm with similar pre-crisis risk profiles. For each Italian firm j, I select the German firm g that minimizes the following RMSE term:

$$g(j) \equiv Argmin_{k\in\mathbb{S}_{\mathbb{C}}} \sqrt{\frac{1}{T}\sum_{t\in\mathbb{P}} \left(dd_{j,t} - dd_{k,t}\right)^2}$$

where $\mathbb{S}_{\mathbb{C}}$ is the sample of non-financial German firms (control group), $\mathbb{P}$ is the pre-crisis period, $T \equiv \mid \mathbb{P} \mid$, $dd_{j,t}$ is the distance-to-default measure for the Italian firm j, and $dd_{k,t}$ is the distance-to-default measure for the German firm k. For each of these pairs, I define *excess corporate risk* as: $C\tilde{R}_{j,t} = CR_{j,t} - CR_{g(j),t}$. The variable $\Delta C\tilde{R}_{j,t}$, therefore, measures the additional change in the corporate risk of firm j, once we control for the corporate risk of a German firm with a similar (pre-crisis) risk profile. The analysis thus helps to purge common factor components that may be operating at the European level.

Figure 3.5: Asymmetric Transmission of Sovereign Risk; Controlling for Global Factors

(a) α_{1h} Coefficients (b) α_{2h} Coefficients



Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks after controlling for German firms (solid black lines). The specification considered is $\Delta\tilde{CR}_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \beta X_t + \gamma_j + \epsilon_{j,t+h}$, where $C\tilde{R}_{j,t} = CR_{j,t} - CR_{g(j),t}$ is the excess corporate risk of Italian firm j after controlling for a German firm $g(j)$ with similar (pre-crisis) risk profile. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. The specification also includes a vector of global controls X_t: log changes in the S&P500 and the VIX index. Panel (a) reports the α_{1h} coefficients over quarters h. Panel (b) shows the α_{2h} coefficients. Quarterly frequency. The dotted lines report the baseline estimates, i.e., without controlling by German firms. Vertical lines report 90% confidence intervals after controlling for German firms. The gray area reports 90% confidence intervals for the baseline case. Standard errors are clustered at the firm and quarter level.

Using the *excess corporate risk* measure, I consider the same Jorda local projection as in Equation (3.1). The estimates are depicted in Figure 3.5 (solid black line). The point estimates for the α_{1h} coefficients are slightly smaller than those of the baseline analysis (on impact, the point estimate is 0.42), suggesting that common factors may have driven part of the increase in risk across Europe. In any case, the estimates are within the 90% confidence interval of the baseline estimate. In terms of the asymmetric transmission, the α_{2h} coefficients are almost unchanged after controlling for German firms.

Robustness and Discussion

In Appendix A.3, I conduct additional tests to asses the robustness of the results. Table A.5 and Figure A.2 show that the results regarding the asymmetric transmission of risk are robust to the inclusion of time fixed effects. While the main analysis has focused on news from Greece and Portugal (as reported in Bahaj, 2020), Figure A.3 shows that the results are robust to different specifications of the news events. In particular, the results, both in terms of magnitudes and persistence, are similar if we include the set of news from Greece, Portugal, Ireland, and Cyprus.

The results are robust to different specifications of the main dependent variable. Given that the left-hand-side variable in Equation (3.1) is given by the absolute change in a firm's corporate risk (i.e., $\Delta CR_{j,t+h}$), a concern behind the reported results is that the asymmetric transmission may be just capturing a proportional increase in risk across all the firms. In Figure A.4, I show that this is not the case. In particular, I consider the same local projection as the one in Equation (3.1) but with $\Delta log(dd_{j,t+h})$ as the dependent variable. The figure shows that safer firms (i.e., those with a larger distance to default) are less affected by the sovereign risk shock. In particular, they experience a smaller drop in their distance to default compared to the average firm.

In the main analysis, I use the distance to default as a measure of non-financial risk given that it allows me to work with a larger sample of firms. The results, however, are robust to alternative measures of corporate risk. In Figure A.5, I consider the effects of a sovereign risk shock on an aggregate index of Italian corporate bond spreads (based on the *Iboxx Corporates Italy* index). The results are in line with those reported in the previous section, albeit slightly smaller. The smaller magnitude of this estimate can be driven by a composition effect: the firms that are constituents of the *Iboxx Corporates Italy* index may be safer than the average firm included in my main analysis.

To shed more light on the role of common factors across firms with different risk profiles, Figure A.6 analyzes how German firms with different (pre-crisis) risk profiles react to the sovereign risk shock. Unlike the case of Italian firms, the majority of the German firms are unaffected by changes in sovereign risk. The exception are those firms above the 80th percentile in terms of pre-crisis default risk for which the estimates are positive and significant. Nevertheless, the point estimate for these German firms is significantly smaller than those of Italian firms.

In terms of the interpretation of the results, even when the foreign news events are orthogonal to 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.

3.4 Channels Behind the Transmission: The Role of Domestic Banks

The analysis so far has shown that changes in sovereign risk lead to changes in corporate risk. In this subsection, I provide suggestive evidence on the importance of banks behind the propagation of sovereign risk to corporate risk. In terms of Equation (4.21), the goal of this analysis is to show that the term $\left(F'_{\eta}G'_{SR}\right)$ is an important driver in the transmission of sovereign risk to non-financial firms. I refer to this mechanism as the *bank-lending channel*. To quantify this channel, I exploit banks' heterogeneity in their exposure to sovereign risk. The underlying idea is as follows. Upon an increase in sovereign risk, the net worth of a bank that is highly exposed to government's bonds decreases significantly, 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.

Data and Analysis

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) as reported by the banks in the sample. This measure of NPLs is, therefore, inclusive of the universe of Italian non-financial firms.

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 of the whole Italian banking sector, covering more than 95% of banks' assets. The main variables used in the analysis are banks' stock of NPLs and their exposure to sovereign risk. Appendix B.1 describes all the variables used in the analysis and provides some summary statistics. 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 challenge is to isolate the bank-lending channel from other (demand-driven) changes that may affect the firms' NPLs. For instance, banks with higher pre-crisis sovereign exposures may have been lending to riskier firms, or to industries and regions that were more affected during the crisis. To control for demand (firm-level) characteristics, the existing literature (Bottero et al., 2020, Farinha et al., 2019, Bentolila et al., 2018, Bofondi et al., 2018, Buera and Karmakar, 2018, and Cingano et al., 2016) 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. Instead, the analysis presented in this section relies on a simpler difference-in-difference framework that exploits within-region banks' heterogeneity. This allows me to capture all the demand-level factors that operate at the regional level and that may be behind the increase in NPLs. Due to these limitations, the estimates of this section may not be interpreted as a causal estimate. Nevertheless, they are still useful as they provide evidence on the role of banks as drivers of sovereign risk. Moreover, the aforementioned papers find that there is no evidence of a systematic sorting between highly exposed banks and the firms most affected by the crisis, which suggests that firm-level factors may not be an important source of bias for the estimates.[22]

Appendix Figure B.1 shows the importance of controlling for regional factors. The figure shows that, at the regional level, there is a clear positive relation between banks' sovereign exposures and the size of the recession. To capture these regional-level factors, banks are sorted across the 20 Italian regions based on the domicile of their headquarters, as reported by the Bank of Italy.[23] Under the assumption of a strong regional bias (i.e, banks only lend to firms operating in their same region), we can then exploit banks' heterogeneity within each region to control for demand-driven characteristics.[24] To this end, I consider the following first-difference regression model:

$$\Delta logNPLS_{i,j,(2008+h)} = \beta_{0,h} + \beta_{1,h} SovExposure_{i,j,2008} + \beta_{2,h} X_{i,j,2008} + \gamma_j + \epsilon_{i,j,(2008+h)}, \tag{3.2}$$

where $\Delta logNPLS_{i,j,(2008+h)}$ measures the change in non-financial NPLs (in logs) for bank i, located in region j, between the base year (2008) and horizon h. The variable $SovExposure_{i,j,2008}$ measures bank i's holdings of sovereign debt at the base year; $\beta_{1,h}$ is our coefficient of interest; $X_{i,j,2008}$ 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), loans, the share of loans to non-financial firms, liquid assets, retail funding, net worth, profits, and reserves. 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.

Results

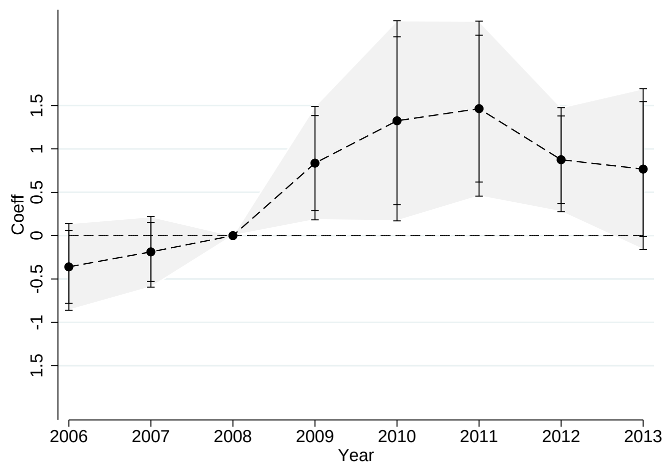
Figure 3.6 shows the OLS estimates and the 95 percent confidence interval for the $\beta_{1,h}$ coefficient in Equation (3.2) for different horizons h. Before 2009, there are no significant

[22] Appendix B.2 discusses these points in more detail.

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

Figure 3.6: Sovereign Exposure and non-financial NPLs



Notes: The figure reports the OLS estimates for the $\beta_{1,h}$ coefficient in Equation (3.2). The dependent variable is: $\Delta log(NPLS_{i,j,2008+h}) \equiv log(NPLs_{i,j,2008+h}) - log(NPLs_{i,j,2008})$, where $NPLS_{i,j,t}$ is the stock of non-financial non-performing loans, as reported by bank i located in region j. The shaded area shows the 95% 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, the share of loans to non-financial firms, liquid assets, retail funding, net worth, profits, and reserves. Annual frequency. Sample includes all the banks included in the ABI dataset after excluding the five largest Italian banks.

differences in the growth rate of NPLs for banks with different sovereign exposure. After 2009, and particularly for 2010 and 2011, the results show a positive and significant relation between the (pre-crisis) 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.

Appendix Table B.3 provides a further description of the estimates for the year 2011. Apart from the sovereign exposure, the bank's share of loans and its capital structure (particularly, its reserves) seem to be the main drivers behind the changes in NPLs. Columns (1) and (4) show the results when no regional dummies are included. As expected, 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 B.2). The estimates are in line with those associated to the finer aggregation level. In Appendix B.3, I describe additional tests to asses the robustness of the results.

Altogether, these results show that, 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. In the next section, I make use of the calibrated quantitative model to formally disentangle the role of banks.

4 Quantitative Analysis

4.1 Numerical Solution

The model described in Section 2 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 (4.19) 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 (see Aldrich et al., 2011). Appendix C.4 describes the algorithm.

4.2 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. Tables 5.1 and 5.2 summarize 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 fixed based on values that are standard in the literature. The value-added share of capital in the Cobb-Douglas production function (α) is set to 0.30, 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.[25] The tax rate τ is set to match an effective corporate tax rate of 27.5%. Lastly, I fix the cost of raising funds $\bar{\varphi}$ to 0.08, which is the value in Gomes (2001).

The rest of the parameters are calibrated to match features of the panel of publicly traded Italian firms described in Section 3 for the pre-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).[26] The discount factor β targets the median profits-to-capital ratio, as it governs the firms' desire to accumulate capital. I target ψ_k and ψ_b to match the within-firm volatility of investment and leverage, respectively. I calibrate λ to target and average recovery rate of corporate loans of 23%, which is the value reported by Banca d'Italia (for unsecured positions). The parameter m_f targets a conservative average corporate loan maturity of 4 years. Lastly, I calibrate the coupon payments c_f and the volatility of the exit shock ν_e to match the average corporate risk (as implied by Merton's distance to default) and the average corporate spread for non-financial Italian firms.[27]

Parameters for the Banks' and Government's Problems. With respect to the parameters governing the banks' problem, I fix banks' discount factor $\tilde{\beta}$, banks' survival rate, and the share of divertible assets κ to standard values in the literature (see, for instance, Bocola (2016) and Gertler et al. (2019)). The parameters governing the sovereign risk process (ρ_s, σ_s, and $s^\star$) are taken from Bocola (2016). These parameters yield an unconditional standard deviation of the model-implied sovereign risk process of 2.20%. As a comparison, the quarterly volatility of the sovereign risk shock is 1.70%.[28]

The other parameters are calibrated to match a set of moments for Italian banks and the Italian government. First, the parameter governing the transfers to the entrant banker γ is calibrated to match the median leverage of the Italian banks in the ABI dataset.[29] 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. The parameter m_G

[25] These three calibrated parameters are similar to those, for instance, in Gilchrist et al. (2014).

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

[27] The target for corporate loan 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).

[28] To make a clearer comparison, both the model-implied sovereign process and the Bahaj sovereign risk shock are normalized by their average values.

[29] 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 non-financial firms relative to banks' net worth.

Table 5.1: Calibration - Firms Parameters

Parameter	Description	Value	Target/Source
	Panel A. Fixed Parameters		
α	Capital Share	0.30	Gilchrist et al. (2014)
χ	Dec. Returns to Scale	0.85	Gilchrist et al. (2014)
δ	Depreciation Rate	0.0275	Annual Rate
τ	Tax Rate	0.275	Corporate Taxes
φ	Cost of Raising Funds	0.08	Gomes (2001)
	Panel B. Calibrated Parameters		
ρ_z	Persistence of TFP	0.95	Firm Distribution
σ_z	Volatility of TFP	0.05	Firm Distribution
β	Discount Factor	0.963	Profits-to-Capital
ψ_k	Capital Adj. Cost	2.00	Investment stdev.
ψ_b	Leverage Adj. Cost	10.00	Leverage stdev.
λ	Recovery Rate	0.10	Firms Recovery Rate
m_f	1/Loans Maturity	0.0625	Loans Maturity
c_f	Coupon	0.03	Credit Spreads - Default Risk
ν_e	Exit Value (stdev)	1.80	Credit Spreads - Default Risk

Notes: This table shows the calibration of the parameters governing the cross-sectional distribution of firms.

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.[30] The parameter Δ_d targets an average recovery value of 50%, which is towards the upper end of the values used in the literature. Lastly, for computational tractability, I assume that the fiscal rule of Equation (4.10) is such that the stock of government's debt B is constant and given by $\bar{B}$. I then set $\bar{B}$ to target the Italian banks' exposure to sovereign risk. In particular, I target the ratio of government's bonds to non-financial loans in the balance sheet of Italian banks.[31]

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 elasticity of Section 3. To this end, I run the same Jorda-style local projection of Equation (3.1) using model-generated data. Surprisingly, the calibrated parameter is in line with previous studies that quantify the productivity losses of sovereign defaults. For instance, based on Argentina's 2001 default, Sandleris and Wright (2014) estimate an aggregate productivity loss of 11.5%.

[30] Debt services include 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.

[31] The assumption is for computational tractability as it allows to decrease the dimension of the state space of the problem. As transfers are lump-sum, alternative fiscal rules have small aggregate implications. In the model, banks only have two assets: sovereign bonds and loans to non-financial firms. I calibrate $\bar{B}$ to match the mean ratio observed in 2007 for the Italian banks in the ABI dataset.

Table 5.2: Calibration - Banks and Government Parameters

Parameter	Description	Value	Target/Source
	Panel A. Fixed Parameters		
$\tilde{\beta}$	Discount Factor	0.99	Standard Value
ψ	Survival Rate	0.95	Standard Value
κ	Share Divertible Assets	0.20	Standard Value
ρ_s	Sovereign Risk Process	0.95	Bocola (2016)
σ_s	Sovereign Risk Process	0.63	Bocola (2016)
$s^{\star}$	Sovereign Risk Process	-7.06	Bocola (2016)
	Panel B. Calibrated Parameters		
γ	Transfer to Entrant Banker	0.55	Banks' Leverage
ζ	Prob. Exit Default	0.10	Duration of Default
m_G	1/Maturity	0.0375	Gov. Maturity
c_G	Coupon	0.037	Debt Services
Δ_d	Default Haircut	0.50	Gov. Recovery Rate
$\bar{B}$	Government Debt	0.80	Banks' Exposure
ξ_D	Aggregate Default Cost	0.90	IV estimate

Notes: This table shows the calibration of the parameters governing the banks' and government's problems.

4.3 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 there are no financial frictions (i.e., banks' stochastic discount factor is equal to the (inverse of) risk-free rate). I then describe moments for the case with aggregate risk and financial frictions.

Non-Stochastic Steady State

Table 5.3 summarizes all the targeted moments for the non-stochastic steady state. 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. It also matches the two targeted moments regarding the within-firm volatility of leverage and investment. With respect to the recovery rate, the model implies a recovery of 21% 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 3.[32] The model does a good job 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

[32]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 5.3: Non-Stochastic Steady State - Targeted Moments

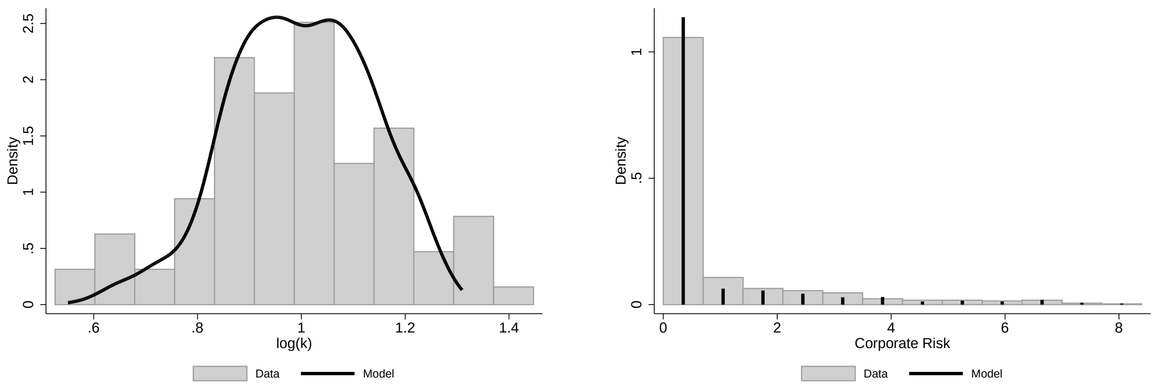
Targeted Moments (Steady State)	Data	Model
$log(k)$: $25th/50th$ percentile	0.879	0.867
$log(k)$: $75th/50th$ percentile	1.136	1.132
Quarterly Profits-to-Capital	0.093	0.104
Leverage (stdev)	0.078	0.074
Investment (stdev)	0.300	0.231
Firms' Recovery Rate	23%	21%
Corporate Risk (mean)	1.84%	1.94%
Firms' Spreads	2.27%	2.15%

Notes: The table shows the set of data moments targeted in the calibration and their model counterpart. The measure of corporate risk is based on Merton's distance-to-default framework.

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

(a) Size

(b) Risk



Notes: The Figure compares the distribution implied by the model and the distribution for the panel of publicly traded Italian firms of Section 3. Panel (a) shows 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. Data for the construction of this variable was retrieved from Datastream. Panel (b) shows the distribution of firms by risk. Both in the model and in the data, corporate risk is given by the Merton's corporate-risk measure. The panel excludes firms with a default risk higher than 8%. The distributions for the Italian data are based on 2009.

Table 5.4: Economy with Sovereign Risk - Targeted and Untargeted Moments

Targeted Moments	Data	Model
Recovery Rate (gov)	50%	50%
Banks' Leverage	5.20	4.80
Banks' share of Gov. Bonds	26.0%	28.5%
$\frac{\Delta CR}{\Delta SR}$	0.42-0.52	0.38
Untargeted Moments	**Data**	**Model**
Firms Leverage (mean)	60%	55%
$\sigma(GDP_t)$	1.45%	2.10%
$\sigma(Investment_t)$	5.27%	9.10%
$\rho\,(SovRisk_{t-1}, GDP_t)$	-0.68	-0.48
$\rho\,(SovRisk_{t-1}, BankLeverage_t)$	0.47	0.21

Notes: The top panel shows the set of data moments targeted in the calibration and their model counterpart. The bottom panel compares selected untargeted moments. Data moments are computed using quarterly data for the 2010-2012 period. Model-implied moments are computed only during periods in which the government is not in default.

already shown in Section 3, 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 4.4.

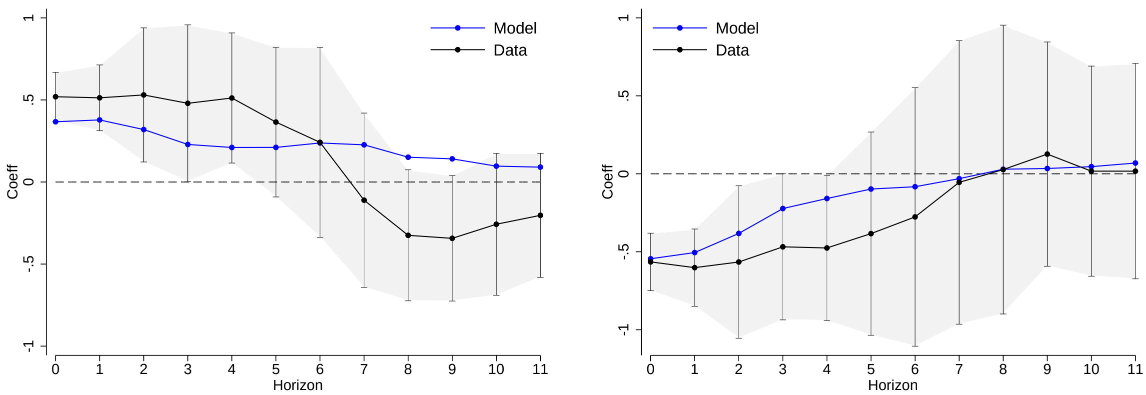
Economy with Aggregate Risk and Financial Frictions

For the economy with aggregate uncertainty and financial frictions, the top panel of Table 5.4 shows that the model closely approximates the targeted moments for the government's recovery rate, banks' leverage, and banks' share of government bonds. Most importantly, the model is able to approximate the empirical estimate for the transmission of sovereign to corporate risk (from Section 3). Figure 5.2 shows that it not only matches the on-impact estimate (which is a targeted moment), but also the persistence of the aggregate effect. In addition, the model is able to mimic the asymmetric transmission of sovereign risk. As in the data, riskier firms are significantly more affected by changes in sovereign risk.

The bottom panel of Table 5.4 shows that the model can also approximate several untargeted moments of the Italian economy. For instance, the average leverage and the volatilities of aggregate output and investment. The model-implied correlations between sovereign risk and output and between sovereign risk and banks leverage are, in magnitude, smaller than the ones observed in the Italian data. This is not surprising given that the model abstracts from any spillover effect from the economy's fundamentals to sovereign risk.

Figure 5.2: IV Coefficients, by Firms with Different Risk - Model vs Data

(a) α_{1h} Coefficients (b) α_{2h} Coefficients



Notes: The figure compares the model-implied dynamics of heterogeneous responses to sovereign risk shocks with the empirical estimates. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h} Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. Blue lines show the model-implied estimates. Black lines show the empirical estimates. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. For the model regressions, the variable ξ_t is given by the model-implied sovereign spread, relative to the risk free-rate. Panel (a) reports the α_{1h} coefficients over quarters h. Panel (b) shows the $\alpha_2 h$ coefficients. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

4.4 Decomposing the Effects & Role of Firm Heterogeneity

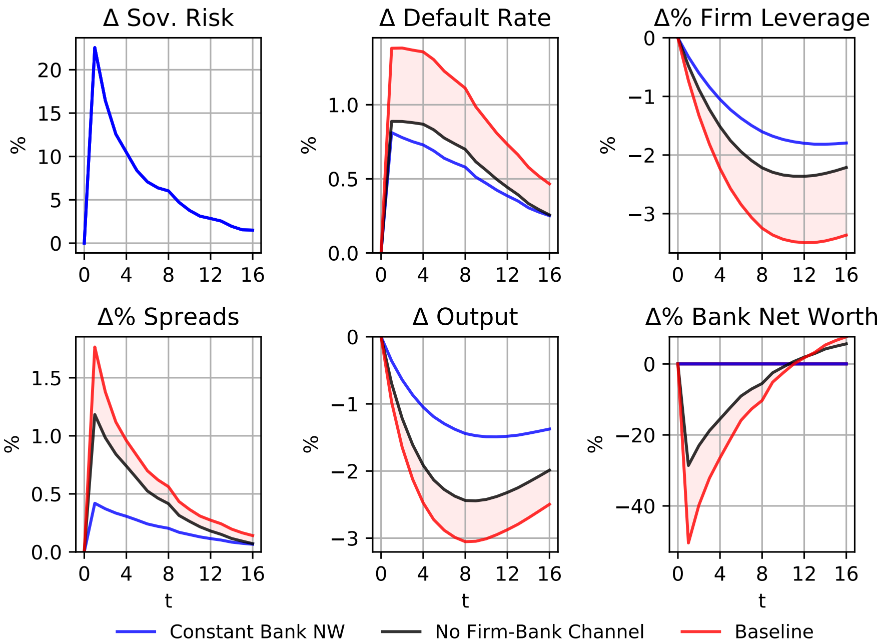
Figure 5.3 presents different counterfactuals to understand the different mechanisms at play. It shows the impulse response of five key variables to a three standard deviation increase in sovereign risk.[33] The blue lines show a counterfactual in which banks' net worth and leverage are constant. Changes in either sovereign or corporate risk have no effect on the credit supply. All the effects are exogenous and are explained by the firms' expected future productivity in the event of a sovereign default (i.e., due to the ξ_D).

The black line shows a counterfactual in which changes in corporate risk do not affect banks' net worth and leverage. Under this scenario, the supply of credit is only a function of sovereign risk. Notice that by its effects on banks' net worth and credit supply, the drop in output is significantly amplified (about 60%). This is the effect already documented in the quantitative literature.

Lastly, the red lines show the impulse response of the baseline model. In this case, corporate risk also affects banks' balance sheets and therefore there is a two-way feedback loop (or doom loop) between corporate risk and banks' net worth. The highlighted red area denotes the additional effects due to this doom loop. Notice that: (i) firms' default rate (thus corporate risk) increases significantly more; (ii) corporate risk contributes to

[33] In all the simulations, the government never defaults.

Figure 5.3: Decomposition of the Effects



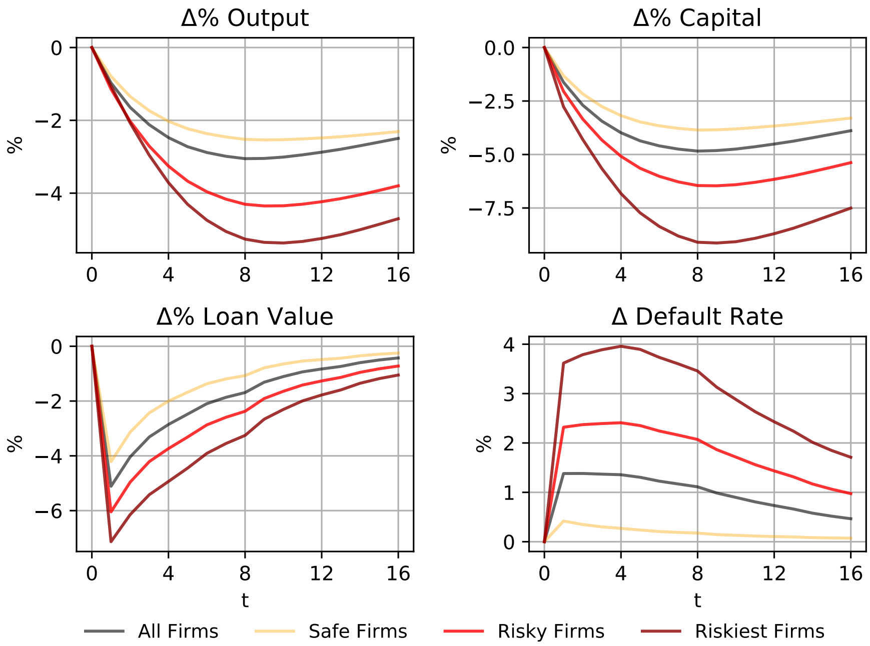
Notes: The figure shows the impulse response to a three standard deviation increase in sovereign risk. Red lines show the results for the baseline model. Blue lines correspond to a counterfactual in which banks' net worth and leverage are constant. Black lines show a counterfactual in which changes in corporate risk do not affect banks' net worth.

almost half of the drop in banks' net worth; and (ii) the doom loop between corporate risk and banks' balance sheets increases the drop in output by an additional 25%. Despite its quantitative importance, the literature has been silent so far on this amplification mechanism.

Taken together, these results show that corporate risk can significantly amplify a sovereign debt crisis. Lastly, I show that policies geared toward riskier firms can significantly dampen this amplification mechanism.

What is the role of firm heterogeneity behind the previous results? Figure 5.4 plots the same impulse response across firms with different levels of default risk (measured before the shock). In line with the results presented in Figure 5.2, the sovereign shock leads to a sharp increase in default rates of high-risk firms but it does not change the default frequency of safer firms. This different response leads to significant differences in the valuation of firms' debt. For the subset of riskiest firms (those above the 80th percentile in terms of default probability), the value of their loans decreases on impact almost twice as much compared to the group of safer firms (those below the 50th percentile). After 4 quarters, the relative difference is even higher. Given that the drop in the valuation of the loan affects banks' net worth, the additional decrease in banks' net worth shown in Figure 5.3 (the red area) is thus mainly driven by higher-risk firms. The right-hand side

Figure 5.4: Heterogeneous Dynamics



Notes: The figure shows the impulse response to a three standard deviation increase in sovereign risk across firms with different (pre-shock) default risk. Black lines show the results across all firms. Yellow lines report the results for firms below the 50th percentile in terms of their (pre-shock) default risk. Light red lines show the results for firms above the 50th percentile. Darker red lines show the case for firms above the 80th percentile. In all the simulations, the government never defaults.

panels show that high-risk firms reduce their stock of capital more, a result that goes in line with the empirical estimates (see Appendix Figure A.1).

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 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.

4.5 Breaking the Amplification Mechanism

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 describing the 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.

I consider a policy intervention that takes into consideration firms' heterogeneous reaction to sovereign risk. As shown in Figure 5.4, 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.

Appendix Figure C.2 shows the results for each of these four policies. The government guarantee scheme, the capital injection to banks, and the homogeneous debt relief program 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 leads to a sharp decline in firms' default rates and further reduces the decline in the aggregate stock of capital. 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 decrease in the default rate and by the smaller drop in the valuation of firms' loans due to the overall reduction in corporate risk.[34] Notice that the drop in banks' net worth attained by this policy is comparable to the policy that directly injects capital into banks.[35] Appendix Figure C.3 provides a decomposition of the effects of the heterogeneous debt relief policy across firms with different levels of risk. The figure shows important spillover effects given that firms that are not directly targeted by the policy also experience a smaller contraction in their investment levels.

[34]While the homogeneous debt relief program also affects 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.

[35]For the government guarantee scheme, the decline in banks' net worth depicted in Figure C.2 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.

5 Conclusion

I present a framework to study the role of firm heterogeneity and financial frictions during sovereign debt crises. I formulate a heterogeneous-firms model in which non-financial firms can endogenously default on their long-term loans. Credit is provided by domestic banks, which are exposed to both sovereign and corporate risk. In the model, exogenous changes in sovereign risk affect firms' default incentives through two different channels. The first channel is endogenous and operates through the domestic banks. An increase in sovereign risk deteriorates banks' balance sheets, decreasing banks' lending capacity. This in turn increases firms' borrowing costs and their incentives to default. The second channel is exogenous and works through firms' lower productivity in the event of a sovereign default. Even if the default is not realized, an increase in sovereign risk decreases firms' expected future productivity, which leads to higher corporate risk.

Because increases in corporate risk also deteriorate banks' balance sheets, the model features a doom loop between corporate risk and banks' net worth. The strength of this doom loop depends on the intensity of the transmission of sovereign risk to corporate risk. Quantifying this transmission is thus crucial to asses the relative importance of the doom loop. I use Italian firm-level data to estimate this transmission and use those estimates to discipline the model. I show that increases in sovereign risk lead to a significant increase in the default probability of non-financial firms: a one-standard deviation increase in a sovereign risk shock leads to a 0.52 percentage points increase in corporate risk. The effects are quite persistent, lasting about five quarters and can account for almost 50% of the total increase in Italian corporate risk. Behind this aggregate transmission, I describe an important asymmetric pass-through of sovereign risk. While, on aggregate, sovereign risk is quickly transmitted to the corporate sector, there is a large heterogeneity across firms behind this transmission. Safer firms, firms with a lower leverage, and firms with a larger share of liquid assets are significantly less affected by changes in sovereign risk.

The calibrated quantitative model is able to reproduce the aggregate transmission of sovereign risk as well as the asymmetric response of corporate risk across firms with different levels of risk. By means of different counterfactuals, I show that during a sovereign debt crisis: (i) corporate risk contributes to almost half of the drop in banks' net worth; and (ii) the doom loop between corporate risk and banks' balance sheets significantly amplifies the drop in output by more than 25%. Taken together, these results show that corporate risk can significantly amplify a sovereign debt crisis.

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A The Transmission of Sovereign to Corporate Risk: Additional Material

A.1 Merton's Distance-to-Default Framework

To measure non-financial firms' default risk, I employ the distance-to-default (DD) framework developed by Merton (1974). This approach views the equity of a firm as a call option on the underlying value of the firm, V. While neither the value of the firm nor its volatility (σ_V) are observable, under two key assumptions, they can be inferred from the value and volatility of the firm's equity and debt.

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

$$\frac{dV}{V} = \mu_V dt + \sigma_V dW, \tag{A.1}$$

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

$$E = V\Phi(\delta_1) - e^{-rT} \times D\Phi(\delta_2), \tag{A.2}$$

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[36]

$$\sigma_E = \frac{V}{E}\Phi(\delta_1)\sigma_V. \tag{A.3}$$

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 (A.2) and (A.3) to map these observed variables into the unobserved components V and σ_V.[37] After we solve for these two variables, the distance to default can be computed as

$$dd = \frac{ln(V/D) + \left(\mu_V - 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}}. \tag{A.4}$$

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

[37] 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 (A.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 (A.1). Third, I update the value of σ_V accordingly until convergence is reached.

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 $CR \equiv \Phi(-dd)$.

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

Using the European Banking Authority (EBA) 2011 Stress Test dataset, Table A.1 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) only accounts for 12% of their total sovereign holdings. Table A.2 shows that Greek and Portuguese banks were not significantly lending to Italian firms. Lastly, Table A.3 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.1: 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: The 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.2: 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: The 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.3: 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: The 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 Additional Results and Robustness

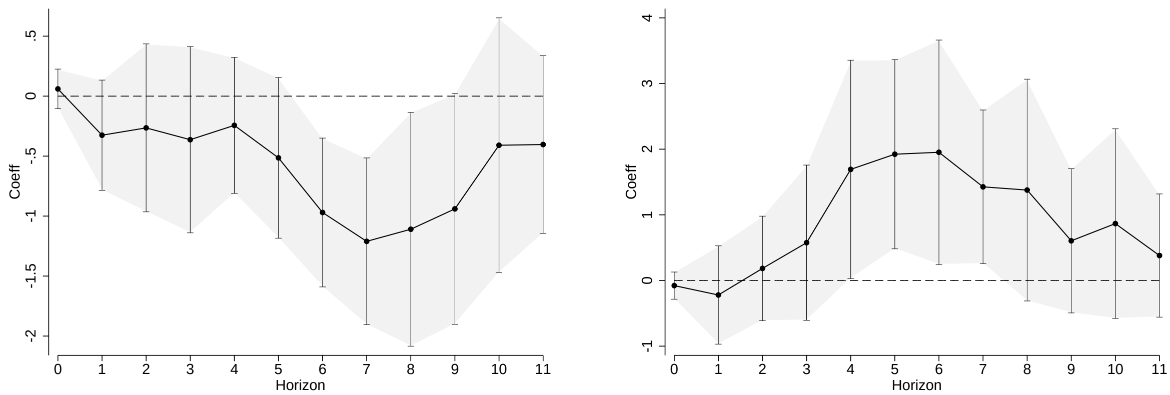
In this Appendix, I present additional results for the main analysis of Section 3. First, I analyze the real implications of the transmission of sovereign risk to the non-financial firms. To this end, I analyze how a firm's investment decision is affected by changes in sovereign risk. In particular, I consider the following Jorda's local projection:

$$Inv_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}, \tag{A.5}$$

where $Inv_{j,t+h} \equiv log(Assets_{j,t+h}) - log(Assets_{j,t-1})$ is the (log) change in a firm's total assets, ξ_t is the sovereign risk shock, $dd_{j,t-1}$ is a firm's distance to default, $Z_{j,t-1}$ is a vector of firm-level controls, and γ_j are firm fixed effects. I use a firm's change in its total

Figure A.1: Asymmetric Transmission of Sovereign Risk; Investment Dynamics

(a) α_{1h} Coefficients (b) α_{2h} Coefficients



Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $Inv_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. The left panel reports the α_{1h} coefficients over quarters h. The right panel shows the α_{2h} coefficients. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

assets as a proxy for its investment, given that variables referring to a firm's stock of capital (for instance, equipment, plant, and machinery) are inconsistently reported. The parameter α_{1h} captures the aggregate (cumulative) change in investment at time $t+h$ to a 1-standard deviation sovereign risk shock at time t. The parameter α_{2h} measures how the response depends on a firm's distance to default at the time of the shock. The results are reported in Figure A.1. On average, an increase in sovereign risk leads to a persistent and significant drop in investment. Moreover, safer firms observe a smaller decline in their investment levels, a result that resembles the one in Ottonello and Winberry (2020).

Table A.4 shows summary statistics for Bahaj's sovereign risk shock, aggregated at a quarterly frequency. Table A.5 presents the details of the estimates reported in Figures 3.3 and 3.4. Importantly, the coefficients for the interaction terms capturing the asymmetric transmission of sovereign risk (i.e., $dd_{j,t-1} \times \xi_t$ and $lev_{j,t-1} \times \xi_t$) are still significant even after controlling for time fixed effects. For completeness, Figure A.2 reports the estimates for the interaction coefficients α_{2h} (at different horizons h) when including time fixed effects.

While in the main analysis I have included only news from Greece and Portugal (as reported in Bahaj, 2020), the results are robust to different specifications of the news events. Figure A.3 considers the same local projection as in Equation (3.1) but the sovereign risk shocks are now constructed based on high-frequency market reactions to news from Greece, Portugal, Ireland, and Cyprus. The results, both in terms of magnitudes and persistence, are similar to those reported in Figure 3.3.

The results are robust to different specifications of the main dependent variable. Given

Table A.4: Italian Reaction to Foreign News Events; Quarterly Frequeny

	Greece	Portugal	G&P
Number of Events (quarters)	12	10	14
Mean Market Reaction (bps)	10.32	-0.18	8.72
Std. Dev. Market Reaction (bps)	15.74	5.85	13.76
Min Market Reaction (bps)	-1.08	-8.50	-4.60
Max Market Reaction (bps)	43.18	13.35	43.45
Total Change (bps)	124	-1.8	122

Notes: The table reports the reaction of Italian spreads around foreign news events. Events are based on Bahaj (2020) and are aggregated at the quarterly frequency. Italian spreads are computed as the difference between the 10-year Italian government bond yield versus the 10-year German government bond yield. Sample period: 2009-2013. QQQ

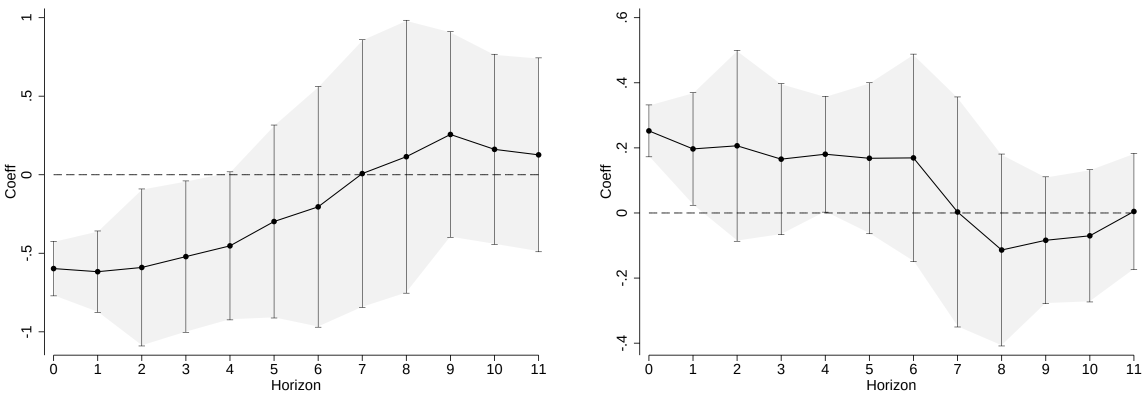
Table A.5: Asymmetric Pass-through of Sovereign Risk

	(1)	(2)	(3)	(4)	(5)	(6)
ξ_t	0.527***	0.520***		0.568***	0.571***	
	(0.069)	(0.070)		(0.079)	(0.082)	
$dd_{j,t-1} \times \xi_t$	-0.567***	-0.565***	-0.597***			
	(0.115)	(0.124)	(0.124)			
$lev_{j,t-1} \times \xi_t$				0.272***	0.252***	0.252***
				(0.081)	(0.079)	(0.078)
Obs.	1,800	1,705	1,705	1,800	1,705	1,705
R^2	0.160	0.201	0.223	0.163	0.179	0.198
Time FE	No	No	Yes	No	No	Yes
Firm Controls	No	Yes	Yes	No	Yes	Yes

Notes: The table shows the heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times a_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. Columns (1)-(3) report the results for the case in which $a_{j,t-1} = dd_{j,t-1}$. Columns (4)-(6) show the results when $a_{j,t-1} = lev_{j,t-1}$. Columns (2) and (4) are the ones reported in the main analysis. All the specifications include firm fixed effects. Columns (3) and (6) further includes quarter fixed effects. Quarterly frequency. Standard errors are clustered at the firm and quarter level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Figure A.2: Asymmetric Transmission of Sovereign Risk; Including Time Fixed Effects

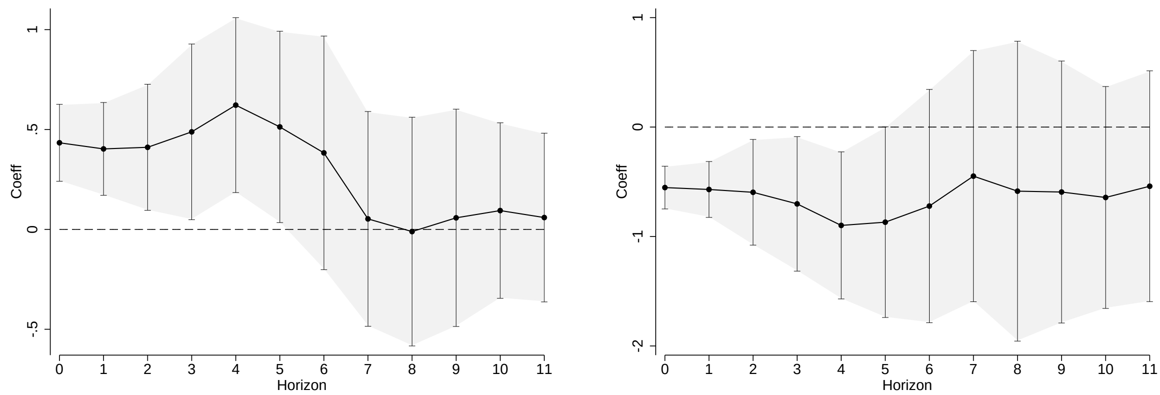
(a) Distance to Default (b) Leverage



Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times a_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \Gamma_t + \epsilon_{j,t+h}$, where Γ_t are time fixed effects. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. Panel (a) reports the α_{2h} coefficients when using $a_{j,t-1} = dd_{j,t-1}$. Panel (b) shows the α_{2h} coefficients for the case in which $a_{j,t-1} = lev_{j,t-1}$. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

Figure A.3: Asymmetric Transmission of Sovereign Risk; Alternative Definition of Events

(a) α_{1h} Coefficients (b) α_{2h} Coefficients

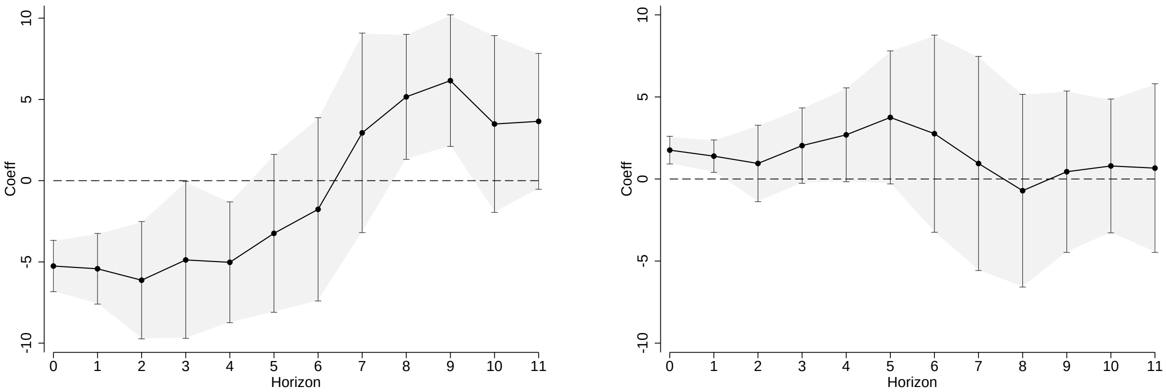


Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal, Ireland, and Cyprus. Panel (a) reports the α_{1h} coefficients over quarters h. Panel (b) shows the α_{2h} coefficients. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

Figure A.4: Asymmetric Transmission of Sovereign Risk; Alternative Measures of Risk

(a) α_{1h} Coefficients

(b) α_{2h} Coefficients



Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta log(dd_{j,t+h}) = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times dd_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. Panel (a) reports the α_{1h} coefficients over quarters h. Panel (b) shows the α_{2h} coefficients. Quarterly frequency. Vertical lines report 90% confidence intervals. Standard errors are clustered at the firm and quarter level.

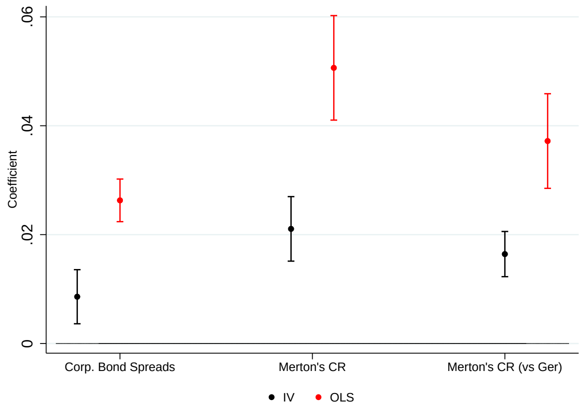
that the dependent variable in the main analysis is the absolute change in a firm's corporate risk (i.e., $\Delta CR_{j,t+h}$), a concern behind the reported results is that the asymmetric transmission may be just capturing a proportional increase in risk across all the firms. In Figure A.4, I show that this is not the case. In particular, I consider the same local projection as in the main text but with $\Delta log(dd_{j,t+h})$ as the dependent variable. The figure shows that safer firms (those with a larger distance to default) are less affected by the sovereign risk shock. In particular, they experience a smaller decrease in their distance to default, compared to the average firm.

The results in the main text are also robust to alternative measures of corporate risk and frequency of the data. In Figure A.5, I consider the daily effects of a sovereign risk shock on Italian corporate bond spreads. In particular, I use the "Iboxx Corporates Italy" which is an index reflecting an average yield for a set of non-financial Italian firms. I then compute the average spread by comparing this index with the yield of a 10-year German bund. Given the lack of firm-level data, the specification I consider is as follows:

$$\Delta C\bar{R}_t = \bar{\alpha_0} + \bar{\alpha_1}\xi_t + X_t + \epsilon_t, \tag{A.6}$$

where $\Delta C\bar{R}_t$ is the average change in Italian corporate risk, ξ_t is the sovereign risk shock, and X_t is a vector of global controls. Results are displayed in Figure A.5. The first column shows the results. As a benchmark, the last two columns display the results based on the distance-to-default measure described in the main text. In all three cases, the estimates based on Bahaj's instrument are significant and positive.

Figure A.5: Comparison with Corporate Bond Spreads



Notes: The figure shows the daily aggregate response to sovereign risk shocks. The specification considered is $\Delta \bar{CR}_t = \bar{\alpha_0} + \bar{\alpha_1}\xi_t + X_t + \epsilon_{j,t+h}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. For the OLS regression, the instrument ξ_t is replaced by the daily change in the 10-year Italian CDS spread. Daily frequency. Vertical lines report 95% confidence intervals. Robust standard errors.

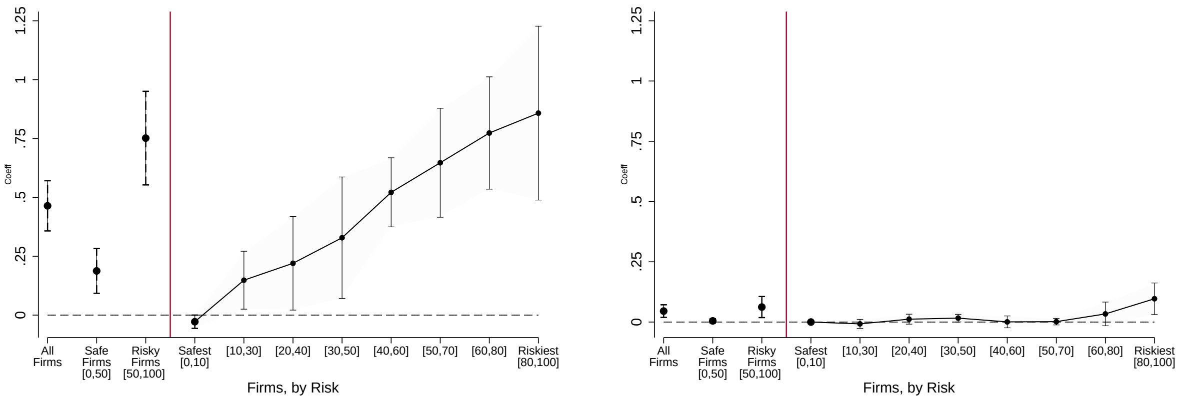
Figure 3.5 in the main text showed that the results are robust after using a set of German firms as a control group. To shed more light on the role of common factor across firms with different risk profiles, I sort firms across different bins (i) based on their pre-crisis risk profile. For each bin i, I consider the following specification:

$$\Delta CR_{j,t}(i) = \alpha_0(i) + \alpha_1(i)\xi_t + \alpha_2(i)dd_{j,t-1}(i) + \alpha_3(i)X_t + \gamma_j(i) + \epsilon_{j,t}(i), \tag{A.7}$$

where $i = \{All, Safest, ...Riskiest\}$ denotes a firm's group, ξ_t is the sovereign risk shock, $dd_{j,t-1}(i)$ is the distance-to-default of firm j that belongs to group i, and X_t is a vector of global controls. Figure A.6 reports the estimates for $\alpha_1(i)$ for the sample of Italian firms (left panel) and German firms (right panel). The point estimates across all the considered bins are significantly smaller for German firms relative to the Italian ones. Even the riskiest German firms are almost unaffected by changes in ξ_t. Figure A.7 considers a similar specification to the one in Equation A.7 and reports the estimate for α_1 when all firms are included in the analysis. The estimates based on the Bahaj instrument are larger for Italy and Spain, which are countries affected by the sovereign debt crisis. While the estimates are still significant for the other countries, suggesting the presence of common factors, the size of the point estimates is smaller than for Italy or Spain.

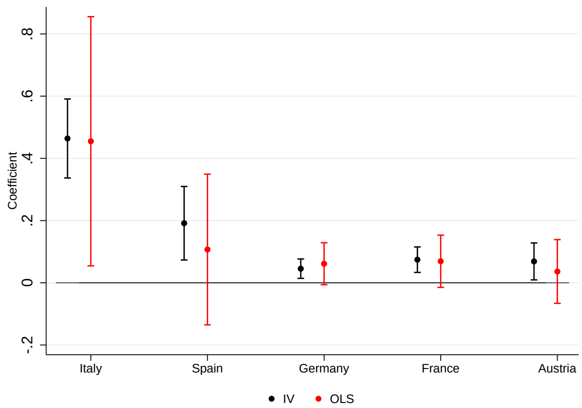
Figure A.6: Heterogeneous Effects, by Firm Risk

(a) Italian Firms (b) German Firms



Notes: The figure reports the heterogeneous responses to sovereign risk shocks. Firms are sorted across different bins (i) based on their pre-crisis risk profile. The specification considered is $\Delta CR_{j,t}(i) = \alpha_0(i) + \alpha_1(i)\xi_t + \alpha_2(i)dd_{j,t-1}(i) + \alpha_3(i)X_t + \gamma_j(i) + \epsilon_{j,t}(i)$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. The vector of global controls X_t includes the (log) change in the S&P500 and the VIX index. Panel (a) shows the estimates for the Italian firms. Panel (b) reports the estimates for the German firms. Quarterly frequency. Grey area depicts the 90 percent confidence intervals. Standard errors are clustered at the firm and quarter level.

Figure A.7: Cross-Country Comparison



Notes: The figure reports the aggregate response to a sovereign risk shock across different European countries. For each country, the specification considered is $\Delta CR_{j,t} = \alpha_0 + \alpha_1\xi_t + \alpha_2 dd_{j,t-1} + \alpha_3 X_t + \gamma_j + \epsilon_{j,t}$. The ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. For the OLS regression, the instrument ξ_t is replaced by the quarterly change in the 10-year Italian CDS spread. The vector of global controls X_t includes the (log) change in the S&P500 and the VIX index. Quarterly frequency. Lines depict the 95 percent confidence intervals. Standard errors are clustered at the firm and quarter level.

B The Role of Bank-Lending Channel: Additional Material

B.1 Data Sources and Definition of Variables

This section describes how the variables used in Section 3.4 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 *BilBank* dataset is highly representative of 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.

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. *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, reserves, 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* is defined as the ratio of a bank's net worth to its total assets. *Reserves* are defined in an analogous way. *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 analysis, I also obtain the following data from the ABI dataset: assets held for trading, assets for sale, payables to other banks, 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 a bank's capital over its total assets. The *Tier1* variable is the one reported in the ABI dataset.

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 direct exposure of banks to Italian government bonds. However, as described in Table A.1, 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. For the analysis in Subsection 3.4, I assume that all sovereign exposures are in fact domestic exposures. On this point, Kalemli-Ozcan et al. (2020) use detailed confidential ECB data and show that there is a strong home bias

Table B.1: Summary Statistics

Variable	Mean	Stdev	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 total banks' loans.

in sovereign holdings across European banks, since around 70% of a bank's government bond holdings consists of domestic bonds. Similarly, Gennaioli et al. (2018) document that banks' 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.

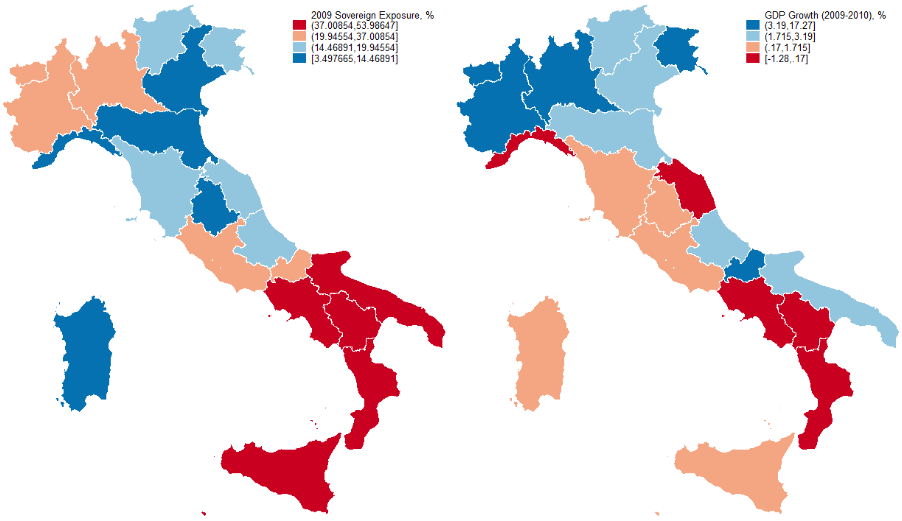
B.2 The Role of Firm-Level Factors

This appendix describes in more detail the limitations of the analysis presented in subsection 3.4. As mentioned in the main text, to control for demand (firm-level) characteristics, the empirical literature on banks' sovereign exposure and its effects on credit supply (Bottero et al., 2020, Farinha et al., 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. 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 paper 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.

Regional Heterogeneity

Figure B.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

Figure B.1: Italian Sovereign Risk and GDP Growth, by Region



Notes: The figure shows 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.

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.

Table B.2 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.[38] 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.

Identifying Assumptions and Interpretation of the Results

If the increase in NPLs is correlated with unobservable firm-specific conditions that also correlate with a bank's sovereign exposure, the OLS specification in Equation (3.2) would deliver a biased estimator for $\beta_{1,h}$. For instance, the estimate would be biased if banks with higher sovereign exposure were systematically lending towards riskier firms or to firms that were more affected during the European debt crisis. More formally, the specification

[38]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.

Table B.2: 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: The table shows summary statistics at the regional level. 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.

in (3.2) allows for unbiased OLS estimates of sovereign exposures on NPLs under three conditions:

(i) 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, which would create a bias in $\beta_{1,h}$. Acharya and Steffen (2015), Bottero et al. (2020), and Buera and Karmakar (2018), among others, provide evidence supporting this assumption.

(ii) Parallel trend assumption: After controlling for the vector of covariates $X_{i,j,2008}$ and a 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 in the main text are in line with this assumption, since they show that the estimate for $\beta_{1,h}$ is not statistically significant before the crisis.

(iii) Absence of firm-level factors: Given that the specification in (3.2) 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 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 a bank's sovereign exposure and its credit supply, 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 a 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 presented in subsection 3.4 may not be interpreted as a causal estimate.

B.3 Additional Results

In this Appendix, I provide additional results and tests for the analysis presented in subsection 3.4. Figure B.2 shows the $\beta_{1,h}$ estimates for the same specification of Equation (3.2) but the left-hand-side variable includes the NPLs of both non-financial firms and other banks' customers. The results are in line with those presented in Figure (3.6), suggesting that the increase in default rates was not specific to the non-financial sector.

The results are robust to alternative specifications of the dependent variable. Figure B.3 shows the results when the dependent variable is defined as:

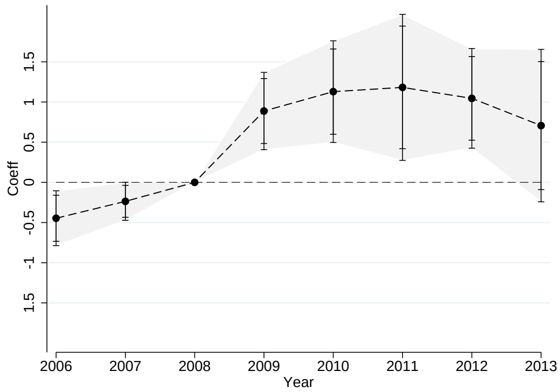
$$\%\Delta NPLS_{i,j,(2008+h)} = \frac{NPLS_{i,j,(2008+h)} - NPLS_{i,j,2008}}{0.5 \times \left(NPLS_{i,j,(2008+h)} + NPLS_{i,j,2008}\right)} \tag{B.1}$$

This growth rate is bounded in the range $[-2, 2]$, which limits the influence of outliers. Bottero et al. (2020) and Buera and Karmakar (2018) use the same standardization. The estimated coefficients are in line with the ones presented in the main analysis (albeit slightly smaller in magnitude).

Table B.3 shows a further description of the estimates reported in Figure B.3. Results are for the year 2011 only. Columns (2) and (5) correspond to the baseline estimates (plotted in Figure B.3). Columns (1) and (4) show the result when no regional dummies are included. 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 B.2).

Figure B.4 presents the results when the dependent variable is measured as the ratio

Figure B.2: Sovereign Exposure and NPLs (total)



Notes: The figure reports the OLS estimates for the $\beta_{1,h}$ coefficient in Equation (3.2). The dependent variable is: $\Delta log(NPLS_{i,j,2008+h}) \equiv log(NPLs_{i,j,2008+h}) - log(NPLs_{i,j,2008})$, where $NPLS_{i,j,t}$ are the stock of non-performing loans, as reported by bank i located in region j. The measure of non-performing loans includes both non-financial NPLs as well as NPLs of other banks' customers. The shaded area shows the 95% 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, share of loans to non-financial firms, liquid assets, retail funding, net worth, profits, and reserves. Sample includes all the banks included in the ABI dataset, after excluding the five largest Italian banks.

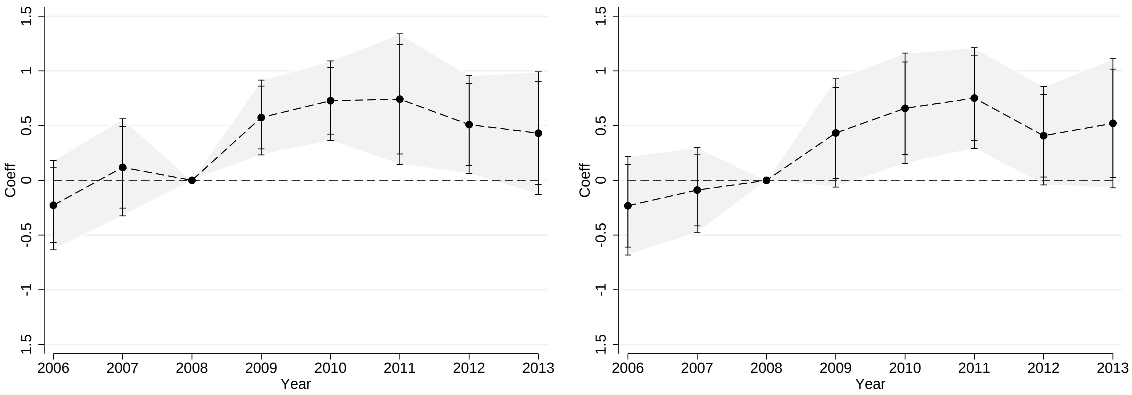
between NPLs and bank's loans:

$$\%\Delta\left(\frac{NPLS}{Loans}\right)_{i,j,(2008+h)} = \frac{\left(\frac{NPLS}{Loans}\right)_{i,j,(2008+h)} - \left(\frac{NPLS}{Loans}\right)_{i,j,2008}}{0.5 \times \left(\left(\frac{NPLS}{Loans}\right)_{i,j,(2008+h)} + \left(\frac{NPLS}{Loans}\right)_{i,j,2008}\right)} \tag{B.2}$$

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.4 is slightly larger than the one described in the main text.

Figure B.3: Sovereign Exposure and NPLs - Dep. Variable: $\Delta\%(NPLS)$

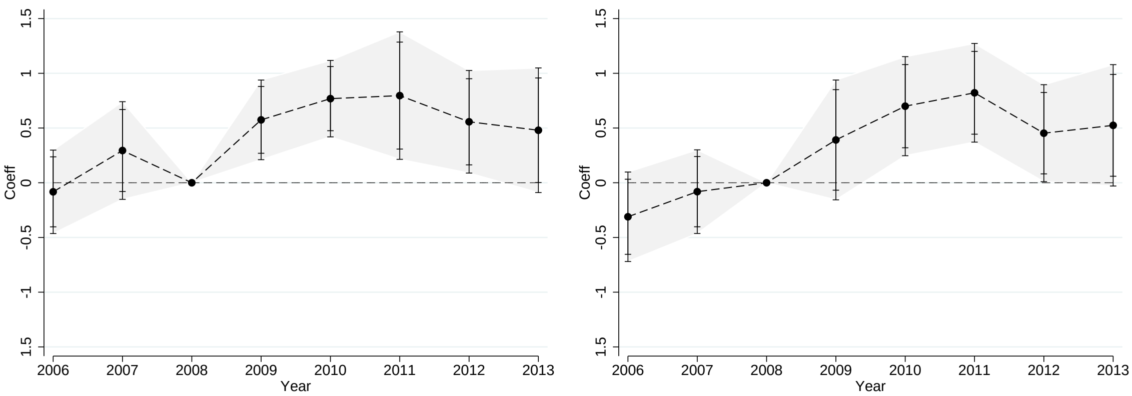
All NPLs | NPLs of Non-financial Firms



Notes: The figure reports the OLS estimates for the $\beta_{1,h}$ coefficient in Equation (3.2). Dependent variable is the $\%\Delta NPLs$, as defined in Equation (B.1). The left panel includes the entire stock of a bank's NPLs, while the right panel includes NPLs of the non-financial sector only. 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.

Figure B.4: Sovereign Exposure and NPLs - Dep. Variable: $\%\Delta\left(\frac{NPLS}{Loans}\right)$

All NPLs | NPLs of Non-financial Firms



Notes: The figure reports the OLS estimates for the $\beta_{1,h}$ coefficient in Equation (3.2). The dependent variable is the $\%\Delta NPLs/Loans$, as defined in Equation (B.2). The left panel includes the entire stock of a bank's NPLs, while the right panel includes NPLs of the non-financial sector only. The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent 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.4 reports the estimates for different sets of bank controls, X_t, and shows that

Table B.3: 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 (3.2) for the 2011 year only. Dependent variable is the $\%\Delta NPLs$, as defined in Equation (B.1). 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.

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.

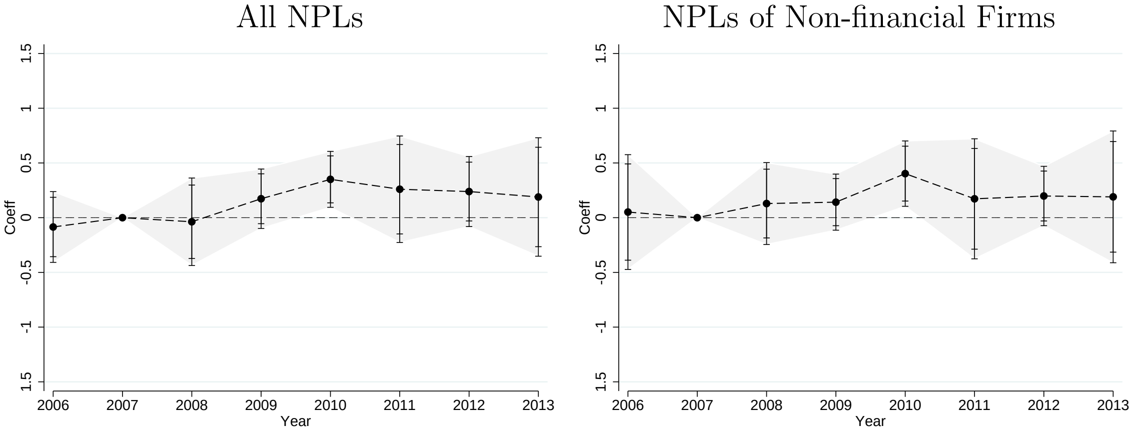
Table B.4: Dependent Variable: %Δ NPLs (non-financial)

	(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 (3.2) for different specifications of the controls. Results are for the 2011 year only. The dependent variable is the $\%\Delta NPLs$, as defined in Equation (B.1). 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.5 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 the 2008 crisis.

Figure B.5: Sovereign Exposure and NPLs - 2007 as Base Year



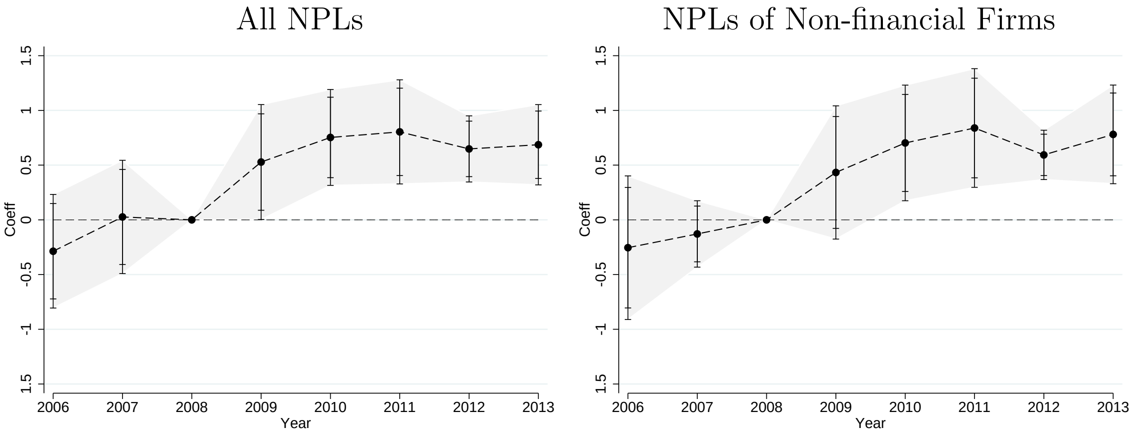
Notes: Figures report the OLS estimates for the $\beta_{1,h}$ coefficient in Equation (3.2), but using 2007 (instead of 2008) as the base year. Dependent Variable: $\%\Delta NPLs_{i,j,h}$ as defined in Equation (B.1). The left panel includes the entire stock of a bank's NPLs, while the right panel includes NPLs of the non-financial sector only. The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). Clustered standard errors 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.

As banks may be operating across different regions and not only in the region where its headquarters are located, Figure B.6 reports the macro-region-level OLS estimates, for different horizons h.[39] 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

[39]This analysis complements the one in Table B.3 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.6: Sovereign Exposure and NPLs - Macro Regions



Notes: Figures report the OLS estimates for the $\beta_{1,h}$ coefficient in Equation (3.2). Dependent Variable: $\%\Delta NPLs_{i,j,h}$ as defined in Equation (B.1). Banks are sorted at the five Italian macro-regions: North-West, North-East, Central, South, and Islands. The left panel includes the entire stock of a bank's NPLs, while the right panel includes NPLs of the non-financial sector only. The shaded area shows the 95 percent confidence interval (vertical lines display the 90 and 95 percent CI). Clustered standard errors at the macro-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.

C The Quantitative Model: Additional Material

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

This section provides a proof for expressions (4.17)-(4.19) 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 (4.16), we get

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

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:

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

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:

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

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

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

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

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

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

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

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

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

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

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

Replacing Equation (C.6) in the slackness condition, we obtain the following Lagrange multiplier

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

Banks' Stochastic Discount Factor and Pricing Kernels

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

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

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

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

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

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:

$$
\begin{aligned}
q\left(k', b', z, \boldsymbol{S}\right) = & \mathbb{E}\Bigg[\Xi\left(\boldsymbol{S'}, \boldsymbol{S}\right)\bigg(\left[1 - h\left(k', b', z', \boldsymbol{S}'\right)\right] \times M_f(k', b', z', \boldsymbol{S'}) + \\
& + h\left(k', b', z', \boldsymbol{S'}\right) \times R\left(k', b', z'\right)\bigg)\Bigg]
\end{aligned}
$$

and

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

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, $M_G(\boldsymbol{S'}) \equiv (1 - m_G)\left(c_G + q_B\left(\boldsymbol{S'}\right)\right) + m_G$.

C.2 Model-implied TFP

The model described in Section 2 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 future productivity with sovereign risk and it is flexible enough to match the increase in corporate risk caused by sovereign risk.

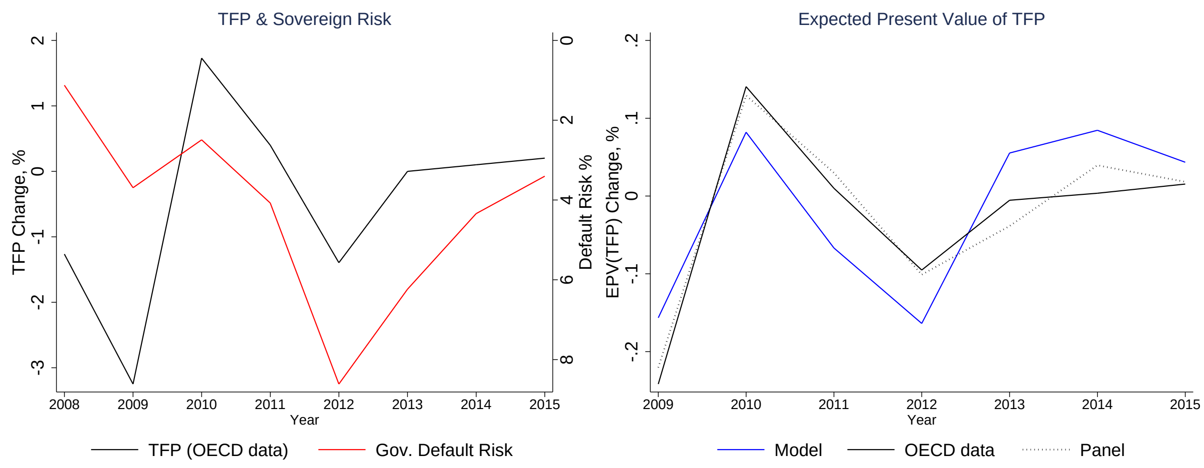
In this appendix, I provide evidence that backs up this modeling strategy. While the goal of this paper is not to formally disentangle the drivers behind changes in sovereign risk and in aggregate TFP, I show that changes in Italy's TFP during the European debt crisis are in fact tightly linked to changes in sovereign risk. Moreover, I show that the model delivers paths of expected future 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.[40] 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

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

[40]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. 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 3). 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.[41] 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 initial value of each simulation, $TFP_{j,t}$, is given by the observed TFP in period t. For

[41]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.

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. I then use this time series to compute a path for the sovereign risk process, $\{s_t\}_{t=2008.q1}^{2015.q4}$.[42] As described in Section 2, this process follows an AR(1) process given by

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

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 $\left\{h^G_{j,t+l}\right\}_{j=1,i=0}^{J,I}$, with the initial condition of $h^G_{j,t} = 0$ for all j. If the government is not in default, the next-period default status is given by

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

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

$$h^G_{t+1} = \begin{cases} 0 & \text{if } \epsilon^e_{t+1} < \zeta \\ 1 & \text{otherwhise,} \end{cases}$$

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

$$\xi_t = \begin{cases} 1 & \text{if } h^G_t = 0 \\ \xi_D & \text{if } h^G_t = 1, \end{cases}$$

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

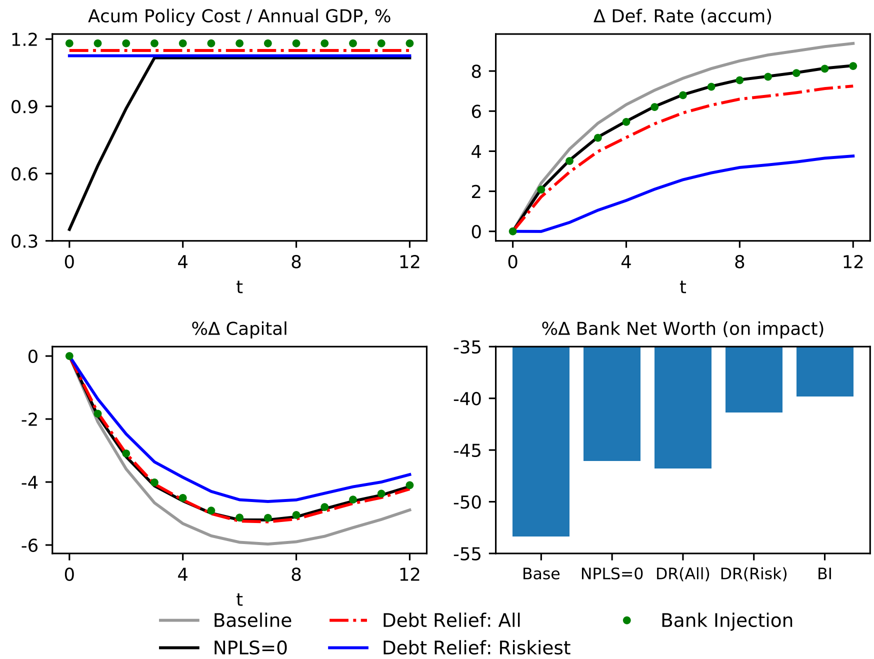
$$EPV_t(\xi) = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=0}^{I}\left(\frac{1}{1+r}\right)^i \xi_{j,t+i} \tag{C.14}$$

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

C.3 Additional Figures

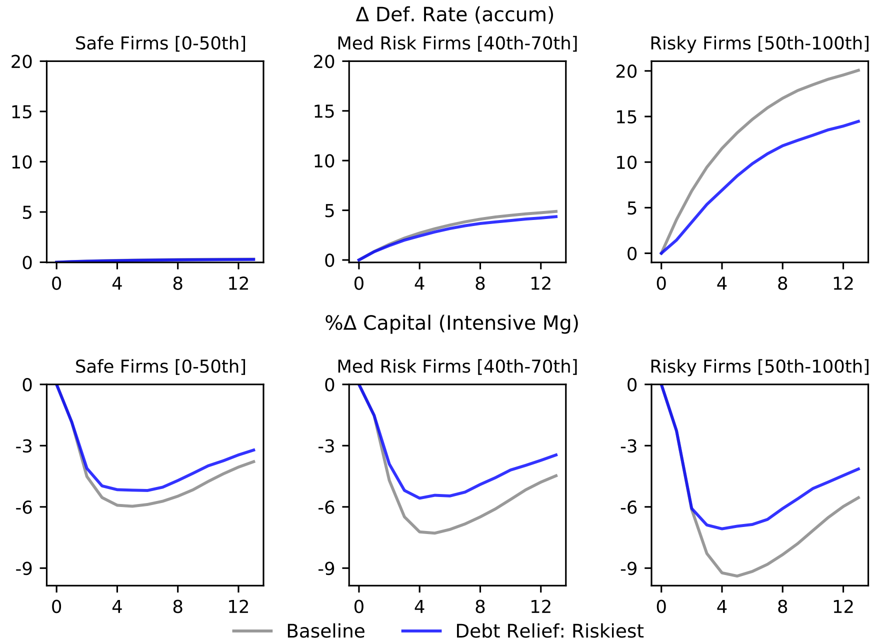
This section presents additional figures regarding the policy analysis of Subsection 4.5. Figure C.2 shows the aggregate implications of the different policies. Figure C.3 provides a decomposition of the effects of the heterogeneous debt relief policy by showing the dynamics for firms with different levels of risk.

Figure C.2: 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).

Figure C.3: 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.

C.4 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. The aggregate state of the problem can be written as $\boldsymbol{S} \equiv (s, h_G, \eta_{-1}, \Omega)$, where s denotes the exogenous sovereign risk process, h_G denotes the government's default status, η_{-1} is the (begging-of-period) banks' net worth, and Ω denotes the firms' distribution across the three idiosyncratic states (k, b, z).[43]

To solve for the equilibrium of the model numerically, I follow a bounded rationality type of approach, as in Krusell and Smith (1998), and use as state variables a set of statistics that summarize the distribution of firms. The distribution of firms is a relevant

[43] As mentioned in Section 4, to reduce the dimensionality of the problem, I assume that the government's exogenous fiscal rule is such that the stock of government debt is constant (if the government is not in default).

variable for a firm's problem because of its implications on banks' stochastic discount factor and loan prices. From Equation (4.19) in the main text, notice that banks' Lagrange multiplier is given by

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

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

Once Υ is included as a state, other moments summarizing the firm distribution are only relevant for forecasting Υ'. However, to keep the model tractable, I assume a forecasting rule independent of other moments of the firm distribution.[44] In particular, I consider the following state-contingent non-linear forecasting rule:

$$\tilde{H}(s, h_G, \Upsilon; s', h'_G) = \begin{cases} e^{a_0 + a_1\Theta(s,s') + log(\Upsilon)} & \text{if } h_G = h'_G = 0 \\ a_2\Upsilon & \text{if } h_G = 0, h'_G = 1 \\ \Upsilon & \text{if } h_G = 1, h'_G = 1, \end{cases}$$

where $\Theta(s, s')$ denotes the change in the government's default probability. In words, I assume a log-linear forecasting rule whenever the government is not in default. If the government is out of a default at time t but defaults at time $t+1$, then I assume a proportional drop in Υ. Lastly, if the government is already in default and the default status does not change, I assume a constant Υ.[45]

Let $\tilde{\boldsymbol{S}} \equiv (s, h_G, \Upsilon)$ denote the aggregate state. Under these assumptions, a firm's

[44]Firms only need (s, h_G, Υ) to infer current loan prices. Adding moments related to the distribution of firms (or other variables summarizing banks' net worth) could potentially improve the forecastability of Υ'. However, I find that adding first-order moments of firms' capital and debt (and banks' deposits) does not significantly improve the forecast of Υ' but further increases the dimensionality of the problem with the consequent increase in computational time.

[45]The latter works well because the probability that the government exits a default is iid.

recursive problem can be written as

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

subject to

$$\begin{aligned}
&d=\pi\left(k,b,z\right)-I\left(k',k\right)+q\left(.,\tilde{\boldsymbol{S}}\right)\times\left[b'-\left(1-m_f\right)b\right]-\left[\left(1-m_f\right)c_f+m_f\right]b+\\
&\quad-\psi_b\left(b',b\right)+e\\
&d\geq 0\\
&\Upsilon'=\tilde{H}\left(s,h_G,\Upsilon;s',h_G'\right),
\end{aligned}\tag{C.15}$$

and subject to Equations (4.12) and (4.13).

The algorithm proceeds in three steps. In the first step, I guess the coefficients of the perceived law of motions for Υ 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 Υ' accordingly. I iterate on these three steps until convergence on the coefficients of the perceived law of motion.

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, 20 points for b, 7 points for z, 6 points for s, and 8 points for Υ. Taking into account the two possible values for h_G, this implies a total of 268,800 state-space points.[46]

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

1. Guess the banks' marginal valuation $\alpha\left(\tilde{\boldsymbol{S}}\right)$ for all $\tilde{\boldsymbol{S}}$.
2. Based on the guessed law of motion for Υ', compute $\alpha\left(\tilde{\boldsymbol{S}}'\right)$ for every possible next-period aggregate state $\tilde{\boldsymbol{S}}'$.
3. Compute $\mathbb{E}\left[\alpha\left(\tilde{\boldsymbol{S}}'\right)\right]$ and $\mu\left(\tilde{\boldsymbol{S}}\right)$.
4. Update $\alpha\left(\tilde{\boldsymbol{S}}\right)$ accordingly and continue until convergence. Compute banks' stochastic discount factor, $\Xi\left(\tilde{\boldsymbol{S}},\tilde{\boldsymbol{S}}'\right)$.

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 $V\left(k,b,z;\tilde{\boldsymbol{S}}\right)$ and the pricing kernel $q\left(k',b',z,\tilde{\boldsymbol{S}}\right)$ for each point of the state space and for each possible choice of (k',b').
2. Taking the pricing kernel as given, solve the firms' problem and update the value function accordingly.

[46] To make a better use of the grid, I re-express the firms' states in terms of capital, leverage (instead of debt), and productivity.

3. Using the optimal policies computed in step 2, update the pricing function.
4. Iterate until convergence of both $V(.)$ and $q(.)$.

As the problem presents several non-convexities, I use a global optimization algorithm to solve for k' and b'. This step of the algorithm relies on the use of graphics processing units (GPUs) to speed up the computations.

The last step of the algorithm consists on simulating the economy in order to update the predicted law of motion. 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. 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 in banks' net worth. In each step of the simulation, I solve for the value of the auxiliary variable $\varUpsilon$ that guarantees market clearing in the loan market. I use a simple bisection algorithm to solve for this variable. I simulate the economy and use the simulated objects to update the coefficients of the perceived law of motion for $\varUpsilon'$. I iterate on this algorithm until convergence of these coefficients.