The Asymmetric Pass-Through of Sovereign Risk

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Abstract

This paper studies the macroeconomic effects of corporate risk during a sovereign debt crisis. I consider a heterogeneous-firms model with endogenous default in which domestic banks are exposed to sovereign and corporate risk. The model features a doom loop between banks' net worth and corporate risk that depends on the transmission of sovereign risk to firms. I use Italian data to estimate this transmission and describe important heterogeneous effects across firms. 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 by more than 25%.

Keywords: Corporate risk, sovereign risk, firm heterogeneity, financial frictions.

JEL codes: E44, F34, G15, G18.

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1 Introduction

Why are sovereign debt crises characterized by large and persistent declines in economic activity? A common explanation in the literature is based on the exposure of domestic financial intermediaries to sovereign risk. Because domestic banks hold a large share of government bonds, increases in sovereign risk weaken banks' balance sheets, tighten the supply of credit to nonfinancial firms, and decrease investment and output.[1] In this paper, I show that this compelling narrative for the effects of sovereign risk on investment and output misses a key ingredient: corporate risk. I show that sovereign debt crises are characterized by large and heterogeneous increases in nonfinancial default risk. An increase in corporate risk not only affects firms' investment and demand for credit, but also decreases banks' net worth due to their exposure to nonfinancial firms. This effect is quantitatively important, given the size of the exposure. For European banks, for instance, loans to the nonfinancial sector are four times larger than their sovereign debt holdings. In this paper, I fill this gap by providing a quantitative model to study the macroeconomic implications of increases in corporate risk during sovereign debt crises.

Disentangling the macroeconomic effects of sovereign and corporate risk is difficult, because they are jointly determined. To this end, I formulate a heterogeneous-firms model with endogenous default in which domestic banks are exposed to both sovereign and corporate risk. In the model, changes in sovereign risk are transmitted to nonfinancial 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 nonfinancial default risk, through its effects on banks' balance sheets, can amplify a sovereign debt crisis.

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 them. I assume that sovereign risk follows an exogenous process, independent of the fundamentals of the economy. The supply of credit is provided by domestic banks, which are owned by households. To finance their

[1] See, for instance, Buera and Karmakar (2021); Bottero et al. (2020); Arellano et al. (2019); Bocola (2016); and Gennaioli et al. (2014).

loans, each bank 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 banks' ability to provide credit. Under this setup, the supply of credit is a function of changes in both sovereign and corporate risk.

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 of defaulting (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, which affects the credit supply and firms' incentives to default. The strength of this doom loop depends on (i) banks' exposure to nonfinancial firms and (ii) the intensity of the transmission of sovereign risk to corporate risk. Quantifying this transmission is thus crucial in order to assess the relative importance of the doom loop.

I use Italian firm-level data to estimate the transmission of sovereign to corporate risk and use those estimates to discipline the model. The main identification challenge 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 a well-identified shock 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 based on a set of "foreign news events" during the European debt crisis. I focus on news events from Greece and Portugal and construct shocks to Italian sovereign risk based on the change in Italian government bond spreads in a narrow 40-minute window around each news event. This identification strategy is similar to the one used in 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 nonfinancial Italian firms using 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 or 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 of firms, each consisting 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 nonfinancial firms. A one-standard-deviation increase in the sovereign risk shock leads to a 0.52 percentage point increase in corporate risk. The effects are quite persistent, lasting about 5 quarters, and can account for about 50% of the observed increase in Italian corporate risk. More importantly, I find an asymmetric transmission of sovereign risk to nonfinancial default risk. Firms with a higher (ex ante) default probability, firms with higher leverage, and firms with a smaller share of liquid assets are significantly more affected by the sovereign risk shock. Lastly, I present suggestive evidence that highlights the role of domestic banks in this transmission. By exploiting banks' heterogeneity in their exposure to sovereign risk, I show that banks with a larger exposure exhibit a larger increase in their counterparty corporate risk (as measured by corporate nonperforming loans, NPLs).

I use the empirical estimates to calibrate the model and use it to study the aggregate implications of the asymmetric transmission of sovereign risk to nonfinancial firms. The quantitative model features several state variables; these include 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 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. I find that the two-way feedback loop between corporate risk and banks' balance sheets significantly amplifies a sovereign debt crisis. Based on different impulse responses to a large sovereign risk shock, I show that (i) corporate risk contributes to almost half of the drop in banks' net worth, and (ii) the doom loop between banks and nonfinancial firms amplifies the drop in output by more than 25%.

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, 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 indirectly affect safer firms, which amplifies the effects of the crisis. I study different policies that can mitigate the negative effects of this doom loop and 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 and benefit safer firms.

Related Literature. The paper relates to several strands of the literature. It combines elements of the empirical literature on the transmission of sovereign risk to the corporate sector with elements of the quantitative literature on the macroeconomic implications of sovereign risk. It is also connected to a broader literature on firm-level responses to aggregate shocks and on the doom loop 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; Gennaioli et al., 2014). The closest study is that of Bocola (2016), who considers a model in which news about a sovereign default decreases banks' net worth, which limits their ability to provide credit and affects the real economy. The main difference with respect to this paper is that I allow for firm heterogeneity and nonfinancial defaults, which generates 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 feedback mechanisms that differ from 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 in 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 banks and nonfinancial firms (Augustin et al., 2018; Almeida et al., 2017; Adelino and Ferreira, 2016; and Acharya et al., 2014).[2] It also connects to a

[2] Almeida et al. (2017) identify this transmission by exploiting the asymmetric variation on corporate

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 nonfinancial firms and analyze its macroeconomic implications.

The paper also connects to the empirical literature on the pass-through of sovereign risk and the role of domestic banks. Buera and Karmakar (2021); Bottero et al. (2020); Kalemli-Ozcan et al. (2020); Bentolila et al. (2018); Bofondi et al. (2018); and Cingano et al. (2016) show that banks with higher (pre-crisis) sovereign risk exposure reduced their credit supply significantly more during the European debt crisis. I contribute to this strand of the literature by showing that banks with higher sovereign exposure also experienced a larger increase in their corporate NPLs.[3]

More generally, the paper relates to a broader literature on the firm-level responses to aggregate shocks that affect firms' borrowing costs. Kroen et al. (2021); Ottonello and Winberry (2020); Cloyne et al. (2019); and Jeenas (2019) are recent examples of papers that study the heterogeneous reactions across nonfinancial firms to monetary policy shocks, based on a firm's market concentration, default risk, age, and liquidity. I complement these studies by analyzing how heterogeneity across nonfinancial firms interacts with financial intermediaries and describe how this interaction can amplify the original shock.

Lastly, the paper is linked to a more general literature on the feedback loop between financial and nonfinancial sectors. Elenev et al. (2020) and Ferrante (2019) are recent examples of general equilibrium models with financial intermediaries and nonfinancial 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 default, which in turn affects banks' balance sheets. My contribution to this literature is to study the role of heterogeneity across nonfinancial firms in this type of feedback loop. The analysis highlights that (ex ante)

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 the credit default swaps (CDS) of nonfinancial European firms. Also using CDS data, Acharya et al. (2014) measure the spillover effects from sovereign risk onto 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.

riskier firms are mainly the ones that affect 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 of the transmission of sovereign to corporate risk and the role of banks in that transmission. Section 4 presents the quantitative analysis, and Section 5 concludes.

2 The Model

I consider a model with incomplete markets and three sectors: a corporate sector formed by heterogeneous firms, a government, and households/bankers. There is a continuum of risk-neutral firms that are heterogeneous in their size, leverage, and productivity. These firms hire labor and use their stock of capital to produce the unique final good of the economy. They can finance the purchases of capital using internal resources or by issuing debt in the form of long-term loans. Firms lack commitment and can default on their loans. A government sector 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 domestic banks, which are owned by households. Bankers use their net worth and households' deposits to finance their loans to firms and purchases of government 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 use 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

$$y = (\zeta z)^{[1-(1-\alpha)\chi]} \times \left(k^{\alpha} l^{1-\alpha}\right)^{\chi}, \tag{2.1}$$

where χ rules the degree of decreasing returns in production, α is the value-added share of capital, ζ refers to the aggregate productivity, and z denotes the idiosyncratic productivity of the firm. The latter follows a continuous Markov process given by $log(z') = \rho_z log(z) +$

$\sigma_z \epsilon'_z$, where $\epsilon'_z \sim N(0,1)$. I assume that firms' aggregate productivity ζ depends on the default status of the government. This variable captures productivity losses faced by firms in the event of a sovereign default, and is given by

$$\zeta = 1 + (\zeta_D - 1)\, h_G, \tag{2.2}$$

where $\zeta_D < 1$ and $h_G = \{0,1\}$ denotes the government's default status.

For a given choice of labor l, profits are given by $\pi = (1-\tau) \times (y - wl)$, where τ is the proportional tax on firms' profits and w denotes the wage. To maintain computational tractability, I abstract from variation in wages and assume that they are constant. After solving for the optimal amount of labor, we can write the profit function as

$$\pi(k,z) = (1-\tau) \times \zeta z k^{\gamma} \times \vartheta(w), \tag{2.3}$$

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

Incumbent firms invest in capital and the accumulation process is subject to adjustment costs. Let δ denote the depreciation rate. The investment function is defined as $I(k',k) \equiv k' - (1-\delta)k + \Psi_k(k',k)$, where $\Psi_k(k',k)$ 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 domestic banks (b), or by issuing new funds (e). 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 $\Psi_b(b',b)$. As in Gilchrist et al. (2014); Cooley and Quadrini (2001); and Gomes (2001), I assume a constant marginal cost of issuing new funds, φ. Let $\bar{\varphi}(e) \equiv e + \varphi \times max\{e, 0\}$.

Firms lack commitment and can default on their stock of loans. In the event of a default, the firm liquidates all of its assets and exits the industry forever (after production takes place). Moreover, the firm's creditors (i.e., banks) retrieve a fraction λ of the value of the firm's production and undepreciated capital. The recovery rate, per unit of loan, is given by

$$R(k,b,z) = \lambda \times \frac{\pi(k,z) + (1-\delta)k}{b}. \tag{2.4}$$

[4] A unit loan of type (m_f, c_f) 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, which simplifies the state space for each firm.

A 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 $q\left(., \boldsymbol{S}\right) \equiv q(k', b', z, \boldsymbol{S})$ 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

$$d = \pi(k, z) - I\left(k', k\right) + q(., \boldsymbol{S}) \times [b' - (1 - m_f)b] - \left[(1 - m_f)\, c_f + m\right] b - \Psi_b\left(b', b\right) + e, \quad (2.5)$$

where the term $q\left(., \boldsymbol{S}\right) \times [b' - (1 - m_f)b]$ denotes the proceeds from issuing new loans and $\left[(1 - m_f)\, c_f + m_f\right] b$ denotes the current debt services. I assume that firms are subject to a nonnegative dividend constraint (i.e., $d \geq 0$).[5] Lastly, firms have an exogenous outside option given by $V^d\left(\nu_d\right) \equiv \nu_d$, where $\nu_d \sim N(0, \sigma_d)$. Under these assumptions, the recursive problem of an incumbent firm is

$$
\begin{aligned}
V^r(k, b, z, \boldsymbol{S}) = Max_{k', b', e} \;\; & (d - \bar{\varphi}(e)) + \beta\, \mathbb{E}_{\left(z', \boldsymbol{S}', \nu_d'\right)|(z, \boldsymbol{S})} \left[max\left\{V^r\left(k', b', z', \boldsymbol{S}'\right), V^d\left(\nu_d'\right)\right\}\right] \\
\text{subject to} & \\
d \geq & 0 \\
\boldsymbol{S}' = & H\left(\boldsymbol{S}\right) \qquad (2.6)
\end{aligned}
$$

and subject to Equation (2.5). The term $V^r\left(k, b, z, \boldsymbol{S}\right)$ denotes the value function for an incumbent firm and $H(\boldsymbol{S})$ denotes the predicted law of motion for the aggregates and for the firm distribution Ω. At the beginning of each period, for a given a realization of ν_d, the firm's valuation is $V\left(k, b, z, \boldsymbol{S}, \nu_d\right) = max\left\{V^r\left(k, b, z, \boldsymbol{S}\right), V^d\left(\nu_d\right)\right\}$. The optimal default policy is thus given by

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

By integrating across the ν_d shock, we obtain the share of defaulting firms for each idiosyncratic state: $h\left(k, b, z, \boldsymbol{S}\right) \equiv \int \tilde{h}(k, b, z, \boldsymbol{S}, \nu_d)\phi(\nu_d)d\nu_d$, where $\phi(\nu_d)$ is the density of a standard normal distribution. It is easy to show that $h\left(k, b, z, \boldsymbol{S}\right) = 1 - \Phi\left(\frac{V^r(k,b,z,\boldsymbol{S})}{\sigma_d}\right)$, where Φ is the cdf of a standard normal distribution. In the event of a default, the firm exits the industry and is replaced by a new entrant. The initial stock of capital and productivity for all entrants are fixed. Let $\{\underline{k}, \underline{b}, \underline{z}\}$ denote the state of a new entrant.

[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.

Let $\mathbb{R}_f(., \boldsymbol{S}') \equiv \mathbb{R}_f(k', b', z', \boldsymbol{S}')$ denote a firm's next-period gross repayment per unit of loan (after integrating across the ν_d shock). 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 next-period optimal policy functions. The pricing kernel is given by[6]

$$q(k', b', z, \boldsymbol{S}) = \mathbb{E}_{(z', \boldsymbol{S}')|(z, \boldsymbol{S})} [\Xi(\boldsymbol{S}', \boldsymbol{S}) \times \mathbb{R}_f(k', b', z', \boldsymbol{S}')], \tag{2.7}$$

where $\Xi(\boldsymbol{S}', \boldsymbol{S})$ is the stochastic discount factor of the domestic banks (to be defined below). From Equation (2.7), it is then clear that a firm's borrowing costs depend on its own probability of default and recovery value, as well as on the banks' discount factor.

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.[7] 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 lump-sum transfers from the government $T(\boldsymbol{S})$ and banks' net proceeds $\Pi(\boldsymbol{S})$. Their

[6] See Appendix C.1 for the derivation.

[7] 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.

recursive problem is given by

$$
\begin{aligned}
& W_h(x, \boldsymbol{S}) = Max_{c,x'}\; c + \tilde{\beta}\, \mathbb{E}_{\boldsymbol{S}'|\boldsymbol{S}}\left[W_h(x', \boldsymbol{S}')\right] \\
& \text{subject to} \\
& \qquad c + x'\frac{1}{R_f(\boldsymbol{S})} = wl(\boldsymbol{S}) + x + \Pi(\boldsymbol{S}) + T(\boldsymbol{S}) \\
& \qquad c \geq 0,
\end{aligned} \tag{2.8}
$$

where $W_h(x, \boldsymbol{S})$ denotes the households' value function. The Euler equation for the households implies that $\tilde{\beta}R_f(\boldsymbol{S}) = 1 + \tilde{\mu}(\boldsymbol{S})$, where $\tilde{\mu}(\boldsymbol{S})$ is the Lagrange multiplier associated with the nonnegative consumption constraint.[8]

2.3 Government

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

$$
\begin{aligned}
PS(\boldsymbol{S}) &\equiv \tau \int \pi(k, b, z, \boldsymbol{S})d\Omega - T(\boldsymbol{S}) \\
&= f_G\left(B\right),
\end{aligned} \tag{2.9}
$$

where $PS(\boldsymbol{S})$ denotes the government's primary surplus and B denotes the stock of government bonds outstanding. Equation (2.9) 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 me 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

$$
q_G(\boldsymbol{S}) \times \left[B' - \left(1 - m_G\right)B\right] + PS(\boldsymbol{S}) = \left[\left(1 - m_G\right)c_G + m_G\right] \times B, \tag{2.10}
$$

[8] In Section 4, I consider a parameterization such that this constraint never binds, which implies a constant risk-free interest rate given by $R_f(\boldsymbol{S}) = 1/\tilde{\beta} \equiv R_f$.

where $q_G(\boldsymbol{S})$ 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 does it has to pay debt services.[9] Assuming that the government is not in default, its next-period gross repayment per unit of debt is given by

$$\mathbb{R}_G(\boldsymbol{S'}) \equiv (1 - h'_G)\, M_G(\boldsymbol{S'}) + h'_G q_G(\boldsymbol{S'})\Delta_d,$$

where $M_G(\boldsymbol{S'}) \equiv (1 - m_G)\,(c_G + q_G(\boldsymbol{S'})) + m_G$, and the next-period default status is

$$h'_G = \begin{cases} 1 & \text{if } \epsilon'_h < s \\ 0 & \text{otherwise,} \end{cases} \tag{2.11}$$

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.[10] As in Bocola (2016), I assume that the process governing the evolution of s is exogenous and orthogonal to the economy's fundamentals. It follows a continuous Markov process given by

$$s' = (1 - \rho_s)\, s^\star + \rho_s s + \sigma_s \epsilon'_s\,;\;\; \epsilon'_s \underset{iid}{\sim} N(0, 1)\,. \tag{2.12}$$

Under these assumptions, the government's pricing kernel is given by

$$q_G(\boldsymbol{S}) = \mathbb{E}_{\boldsymbol{S'}|\boldsymbol{S}}\left[\varXi\,(\boldsymbol{S'}, \boldsymbol{S}) \times \mathbb{R}_G(\boldsymbol{S'})\right]. \tag{2.13}$$

2.4 Bankers

Let η denote a bank's net worth after the default decisions (by firms and the government) have been made. A banker uses its net worth η and households' deposits x' to issue loans to firms and buy government bonds. Exit is stochastic, occurring with an exogenous probability $(1 - \psi)$. A banker that exits becomes a worker and is replaced by a worker

[9] To satisfy its budget constraint while in default, the government adjusts households' transfers so that $PS(\boldsymbol{S}) = 0$.

[10] If the government is currently in default, the gross repayment per unit of debt is $\mathbb{R}_G(\boldsymbol{S}) \equiv q_G(\boldsymbol{S})$. At the beginning of each period, the government exits default with probability ς_e. Its next-period default status is thus given by

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

where ϵ'_{exit} is a uniformly distributed random variable.

from his household.[11] 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 its assets. For lenders to be willing to supply funds to the banker, the following incentive constraint must be satisfied:

$$\kappa\left(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B'\right) \leq W\left(\eta,\boldsymbol{S}\right), \tag{2.14}$$

where $\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega$ denotes the value of loans made to the nonfinancial firms, $q_G(\boldsymbol{S})B'$ is the value of the sovereign debt holdings, and $W(\eta,\boldsymbol{S})$ denotes the valuation of a banker with net worth η. A banker's recursive problem is given by

$$\begin{aligned}
W(\eta,\boldsymbol{S}) &= Max_{x',B',b'(.)}\ \tilde{\beta}\,\mathbb{E}_{\boldsymbol{S}'|\boldsymbol{S}}\left[(1-\psi)\,\eta' + \psi W(\eta',\boldsymbol{S}')\right]\\
\text{subject to}\quad & \\
&\frac{1}{R_f\left(\boldsymbol{S}\right)}x' + \eta = \int q\left(.,\boldsymbol{S}\right)b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B'\\
&\eta' = -x' + \int \mathbb{R}_f(.,\boldsymbol{S}')b'(.,\boldsymbol{S})d\Omega + \mathbb{R}_G(\boldsymbol{S}')B'\\
&\kappa\left(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B'\right) \leq W\left(\eta,\boldsymbol{S}\right)\\
&\boldsymbol{S}' = H\left(\boldsymbol{S}\right).
\end{aligned} \tag{2.15}$$

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 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 its net

[11] 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.

worth: $W(\eta,\boldsymbol{S}) = \alpha(\boldsymbol{S}) \times \eta$. The bank's marginal valuation $\alpha(\boldsymbol{S})$ is given by

$$\alpha(\boldsymbol{S}) = \tilde{\beta} R_f(\boldsymbol{S}) \frac{[(1-\psi) + \psi \mathbb{E}\alpha(\boldsymbol{S'})]}{1-\mu(\boldsymbol{S})}, \tag{2.16}$$

where $\mu(\boldsymbol{S})$ is the Lagrange multiplier of the incentive constraint and can be written as

$$\mu(\boldsymbol{S}) = Max \left\{ 1 - \frac{\tilde{\beta} R_f(\boldsymbol{S}) [(1-\psi) + \psi \mathbb{E}\alpha(\boldsymbol{S'})]}{\kappa \Big(\int q(.,\boldsymbol{S}) b'(.,\boldsymbol{S}) d\Omega + q_G(\boldsymbol{S}) B' \Big)} \eta \, , \, 0 \right\}. \tag{2.17}$$

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

$$\Xi(\boldsymbol{S'},\boldsymbol{S}) \equiv \frac{\tilde{\beta}\Lambda(\boldsymbol{S'})}{\mu(\boldsymbol{S})\kappa + \tilde{\beta} R_f(\boldsymbol{S}) \mathbb{E}\Lambda(\boldsymbol{S'})}, \tag{2.18}$$

where $\Lambda(\boldsymbol{S'}) \equiv (1-\psi) + \psi\alpha(\boldsymbol{S'})$. From Equation (2.18), notice that the discount factor depends not only on whether banks' leverage constraint is currently binding (i.e., $\mu(\boldsymbol{S}) \geq 0$) but also on the 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' SDF, since they affect the likelihood that the constraint may bind in the future.

2.5 Definition of Equilibrium

Let $\boldsymbol{S} = (s, B, \eta, h_G, \Omega)$ denote the aggregate state space, where s is the sovereign risk process, B is the government's stock of debt, η 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 $\{W_h(x,\boldsymbol{S})\}$, and bankers $\{W(\eta,\boldsymbol{S})\}$; (ii) a set of policy functions for firms $\{k'(.,\boldsymbol{S}),\, b'(.,\boldsymbol{S}),\, h(.,\boldsymbol{S})\}$, households $\{c(.,\boldsymbol{S}), x'(.,\boldsymbol{S})\}$, and bankers $\left\{\hat{b}'(.,\boldsymbol{S}),\, \hat{B}'(.,\boldsymbol{S}),\, \hat{x}'(.,\boldsymbol{S})\right\}$; (iii) pricing functions $\{R_f(\boldsymbol{S}), q(.,\boldsymbol{S}), q_G(\boldsymbol{S})\}$; and (iv) a perceived law of motion for the aggregates $H(\boldsymbol{S})$

[12] To avoid complicating the notation, I also denote the banks' aggregate net worth with η.

such that:

1. Given prices and $H(\boldsymbol{S})$, 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 bonds, deposits, and goods clear.
4. $H(\boldsymbol{S})$ is consistent with agents' optimization.

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.[13] On the other hand, this modeling strategy has the advantage that the sovereign risk process of Equation (2.12), together with the reduced-form productivity loss of Equation (2.2), is 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 is endogenous and operates through 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 (2.17) and (2.18), 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. As shown in Equation (2.2), I assume an exogenous efficiency cost for the corporate sector in the event of a sovereign default. This efficiency cost 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.[14] 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.[15]

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

[14] See Borensztein and Panizza (2009) for a general discussion of different channels through which sovereign risk can affect nonfinancial 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.

[15] In Appendix C.2, I show that changes in Italy's TFP during the European debt crisis were tightly

In addition to 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 decrease banks' net worth η, which affects banks' stochastic discount factor (as shown in Equations (2.17) and (2.18)) and increases firms' borrowing costs (by lowering $q(., \boldsymbol{S})$). From the firms' recursive problem in Equation (2.6), notice that a lower $q(., \boldsymbol{S})$ decreases $V^r(k, b, z, \boldsymbol{S})$, which in turn increases the likelihood of a default.

For illustrative purposes and to better understand the mechanisms at play, suppose that we can summarize the model in the following nonlinear system of equations:

$$\eta = \Phi(SR, CR)$$
$$CR = \Gamma(SR, \eta).$$

By totally differentiating these two expressions and after combining terms, we have that

$$\frac{\Delta CR}{\Delta SR} = \left(\Gamma'_{SR} + \Phi'_{SR}\Gamma'_{\eta}\right) \times \frac{1}{1 - \Phi'_{CR}\Gamma'_{\eta}}. \tag{2.19}$$

The term Γ'_{SR} refers to the direct transmission of sovereign to corporate risk. In the model, it operates through the exogenous decrease in firms' productivity upon a sovereign default. The $\Phi'_{SR}\Gamma'_{\eta}$ term captures the endogenous transmission of sovereign risk through domestic banks. This transmission depends on the banks' exposure to sovereign risk and on the sensitivity of corporate risk to changes in banks' net worth. Lastly, the term $\frac{1}{1-\Phi'_{CR}\Gamma'_{\eta}}$ captures the amplification mechanism that arises due to the feedback between banks' net worth and corporate risk.

In the next section, I use Italian data to estimate the transmission of sovereign risk to corporate risk. In Section 4, I use those estimates to discipline the quantitative model. I then use the calibrated model to disentangle the different channels behind this transmission and quantify their aggregate implications.

3 Empirical Analysis

I use Italian firm-level data to estimate the transmission of sovereign risk to nonfinancial firms. The goal of the analysis is twofold. First, I estimate the aggregate transmission of sovereign risk to corporate risk and describe a large heterogeneity across firms behind

connected with Italian sovereign risk. Moreover, the reduced-form productivity loss of Equation (2.2) delivers paths of expected future TFP similar to those observed in the data.

this transmission. Second, I provide evidence on the role of domestic banks in this transmission.

3.1 Data Sources and Construction of Corporate Risk

The analysis relies on high-frequency Italian firm-level data. To quantify corporate risk, I retrieve financial data for all publicly traded nonfinancial Italian firms that were active (at least) during the 2007-2013 period. Data were retrieved from Bloomberg and Compustat. I use Bloomberg for daily data on the stock prices and shares outstanding for each firm. I use Compustat to get firms' quarterly balance-sheet data. The main variables in the analysis are total assets, liabilities (short- and long-term), liquid assets, and sales. Appendix A.1 describes the variables used.

To measure nonfinancial firms' default risk, I employ the distance-to-default framework developed by Merton (1974).[16] 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).

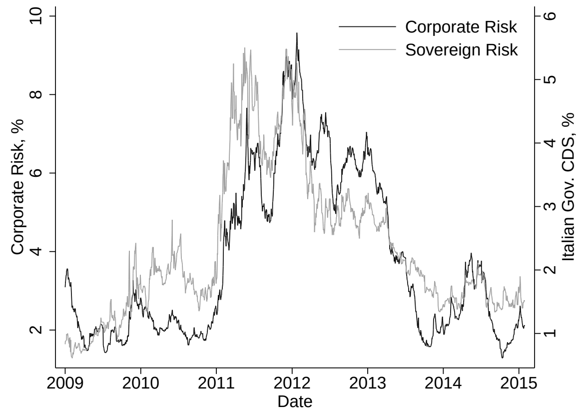
Merton's framework views the equity of a firm as a call option on the underlying value of the firm. While neither the value of the firm nor its volatility are directly observable, under the model's assumptions, both can be inferred from the value and volatility of the firm's equity and capital structure. In Merton's model, a firm defaults whenever $log(V_{j,t}/D_{j,t}) < 0$, 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 deviations by which the $log(V_{j,t}/D_{j,t})$ 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.2).

The left panel of Figure 3.1 shows the constructed measure of Italian corporate risk, together with the Italian government's CDS. There is a clear positive correlation between sovereign and corporate risk. In particular, between April 2010 (first Greek bailout) and late 2012, both measures of risk increased sharply. The right panel shows the evolution of Italian corporate risk for firms with different (pre-crisis) 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

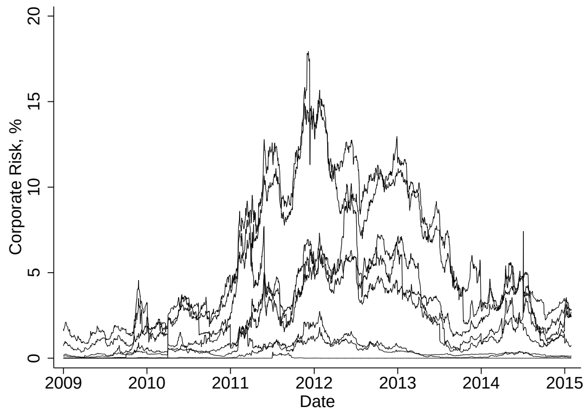
[16] The distance-to-default framework has been used extensively in the literature. See, for instance, Bharath and Shumway (2008); Gilchrist and Zakrajšek (2012); and Ottonello and Winberry (2020).

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 nonfinancial 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 bins based on their default risk in 2009. Results for the first 8 bins (safer firms) are included in the graph.

a larger increase in their default probability during the crisis period.

3.2 Identification Strategy

The main challenges when estimating the transmission of sovereign to corporate risk are that (i) sovereign risk may increase in response to the 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 overcome these challenges, I focus on high-frequency market reactions around a set of specific events. To this end, I employ a well-identified shock constructed by Bahaj (2020) that isolates exogenous changes in sovereign risk.

Bahaj's (2020) 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 the Bloomberg newswire, Bahaj is able to precisely time (at the minute) when these events happened and create narrow windows around each news event. Based on this set of news, he then constructs 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 event in country Y.[17]

To avoid potential endogeneity issues, foreign interventions (for instance, an ECB or IMF announcement) and events that directly relate to the sovereign bond market (in particular, credit rating downgrades) are excluded from the analysis. 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. Second, rating announcements are omitted because 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.

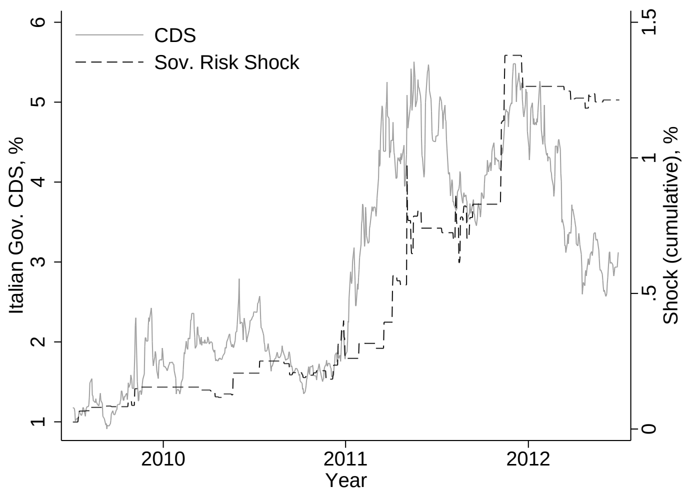
For the analysis in this section, I focus on the set of news events in Greece and Portugal listed by Bahaj (2020). The sovereign risk shock, ξ_t, is given by the change in the 10-year Italian government credit spread (relative to the German bund) in a narrow 40-minute window around each foreign news event. 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. Appendix Table A.5 provides some summary statistics of the sovereign risk shock.

There are three underlying assumptions behind the identification strategy. The first is that the foreign news from Greece and Portugal has a sizable effect on Italian sovereign risk. This indeed 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., 2017); or fear of euro exit and redenomination risk (Krishnamurthy et al., 2018).

The second assumption is that Italian firms are not directly affected by the foreign news events apart from the effect through changes 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 me to identify the causal link of sovereign risk on corporate risk. This is a reasonable assumption, given the weak trade

[17]The majority of the news events in the dataset include announcements or statements to the press from an official government source. Local news events 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 reflect the market's response to a fiscal news shock. For similar reasons, Euro-area news events are also excluded from the analysis.

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 10-year Italian government credit default swaps (CDS). Variables are reported at a daily frequency.

and financial linkages between Italy and these two countries.[18] Bahaj (2020) provides a formal analysis showing that countries' interlinkages have no explanatory power over relative market reactions to the news events. A third assumption is that the foreign news events do not affect common factors behind the pricing of sovereign and corporate risk. Given that these news events may have triggered a change in risk aversion or in the market price of risk across Europe, I use a sample of nonfinancial German firms to control for potential common shocks.

3.3 Framework and Results

I am 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

[18]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.2-A.4 in Appendix A.3 provide supporting evidence.

Jorda (2005)-style local projection:

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

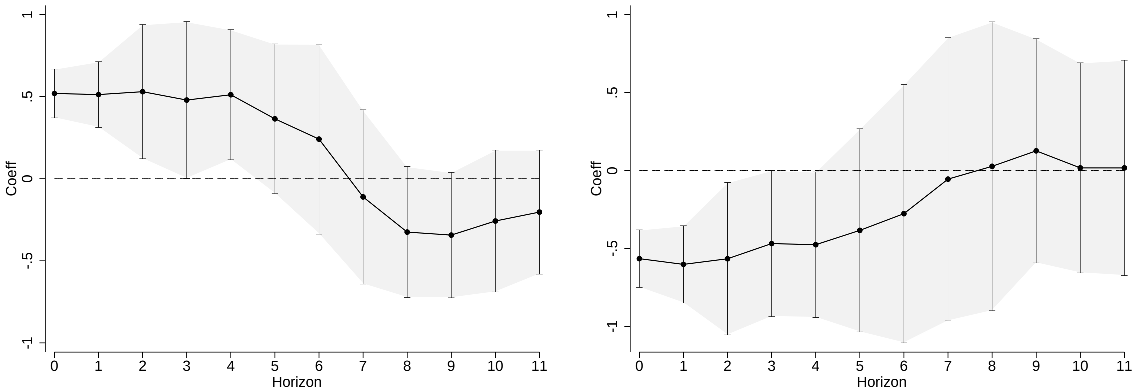
where $\Delta CR_{j,t+h}$ is the cumulative change in the corporate risk of firm j at horizon h, ξ_t is the sovereign risk shock, $a_{j,t-1}$ is the firm's financial position, $Z_{j,t-1}$ is a vector of firm-level controls, and γ_j are firm fixed effects. The vector $Z_{j,t-1}$ includes the level of $dd_{j,t-1}$ 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 a firm's financial position at the moment of the shock. I use three 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 $dd_{j,t-1}$ as a firm's financial position. Panel (a) shows the estimates for the α_{1h} coefficients. On impact, a 1-standard-deviation increase in the sovereign risk shock leads to an additional 0.52 pp increase in aggregate corporate risk. The effects are quite persistent, lasting about 5 quarters. A back-of-the-envelope calculation suggests that these estimates can explain about 50% of the observed increase in Italian corporate risk.[19] Panel (b) shows the estimates for the α_{2h} coefficients. Firms whose distance to default is 1 standard deviation above the average (i.e., safer firms) are significantly less affected by sovereign risk. Notice that $\alpha_{1,h} + \alpha_{2,h}$ is close to zero, which indicates 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. In Appendix A.4, I show that all of these results are robust to the inclusion of time fixed effects.

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

Figure 3.3: Asymmetric Transmission of Sovereign Risk; Dynamics

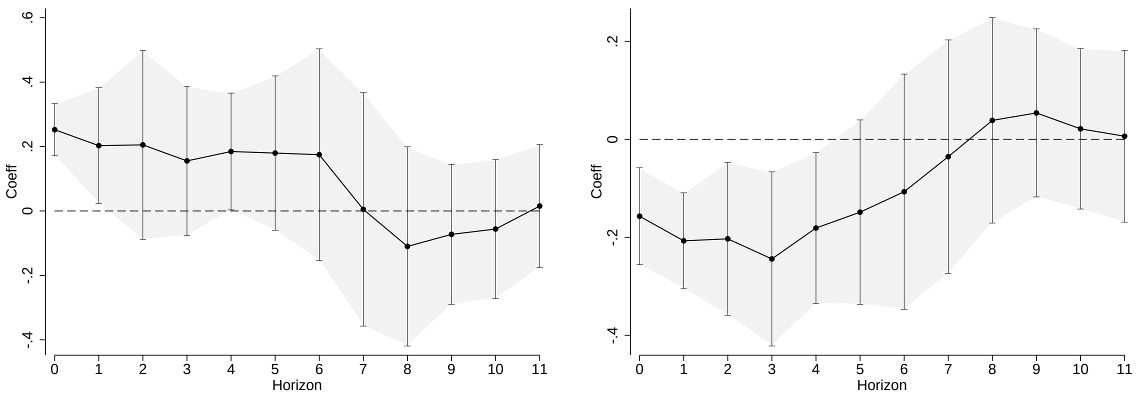
(a) α_{1h} Coefficients (b) α_{2h} Coefficients



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.

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.

Taken together, these results highlight the presence of an asymmetric transmission of sovereign risk. Whereas in aggregate, sovereign risk is quickly transmitted to the corporate sector, safer firms, firms with smaller leverage, and firms with a larger share of liquid assets are significantly less affected. In Appendix A.4, I show that this asymmetric transmission has important real consequences. In particular, for a given increase in sovereign risk, I find that riskier firms decrease their investment significantly more relative to safer firms.

The Role of Common Factors and Robustness

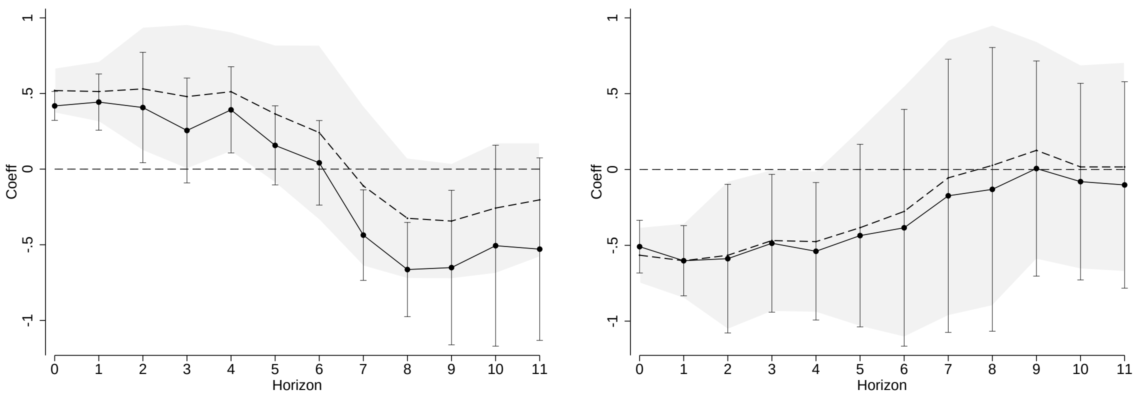
An important concern with respect to the previous analysis is that the foreign news events may have triggered a change in risk aversion or in the market price of risk across Europe. If that were the case, the previous estimates would be biased, because they would be capturing the comovement between sovereign 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 nonfinancial German firms to control for changes in common factors. In particular, I create pairs of firms, each consisting of one Italian and one German firm with similar pre-crisis risk profiles. For each Italian firm j, I select a German firm g such that: $g(j) \equiv Argmin_{k \in \mathbb{S}_{\mathbb{C}}} \sqrt{\frac{1}{T} \sum_{t \in \mathbb{P}} (dd_{j,t} - dd_{k,t})^2}$, where $\mathbb{S}_{\mathbb{C}}$ is the sample of nonfinancial German firms (control group); $\mathbb{P}$ is the pre-crisis period; $T \equiv | \mathbb{P} |$; $dd_{j,t}$ 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 pair, 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 I 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. Using the *excess corporate risk* measure, I consider the same 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), which suggests 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 estimates. In terms of asymmetric transmission, the α_{2h} coefficients are almost unchanged after controlling for German firms.

In Appendix A.4, I conduct additional tests to assess the robustness of the results. I show that the sovereign risk shock at time t is not related to changes in corporate risk at

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 $\tilde{CR}_{j,t} = CR_{j,t} - CR_{g(j),t}$ 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&P 500 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.

time $t - h$, for $h \geq 1$. I show that the results are robust to the inclusion of news events from Greece, Portugal, Ireland, and Cyprus. The results are also robust to different specifications of the main dependent variable. In particular, I show that the results are analogous when using $\Delta log(dd_{j,t+h})$ as the dependent variable. I also consider the effects of sovereign risk on a daily index of Italian corporate bond spreads *(Iboxx)*. The results are in line with those based on Merton's distance to default, albeit slightly smaller.[20] Lastly, to shed more light on the role of common factors, I analyze how German firms with different (pre-crisis) risk profiles react to the sovereign risk shocks. Unlike the case of Italian firms, the majority of the German firms are unaffected by changes in sovereign risk. The exception is those firms above the 80th percentile in terms of pre-crisis default risk, for which the estimates are positive and significant. Nevertheless, the point estimates for these German firms are an order of magnitude smaller than those for Italian firms.

[20]The smaller estimates may be explained by a composition effect: Firms that are constituents of the *Iboxx Corporates Italy* index may be safer than the average firm included in my main analysis.

3.4 The Role of Domestic Banks

In this section, I provide suggestive evidence on the role of domestic banks in the transmission of sovereign risk to nonfinancial firms. I refer to this mechanism as the *bank-lending channel*. The analysis relies on bank-level data to exploit banks' heterogeneity in their exposure to sovereign 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 for high-frequency data), in this section I use corporate nonperforming loans (NPLs) as reported by the banks in the sample. This measure of NPLs, therefore, is inclusive of the universe of nonfinancial Italian firms.

Two datasets are used. First, I use annual balance-sheet data for commercial, cooperative, and popular banks headquartered in Italy during the 2005-2013 period. To this end, I use 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.[21] The second dataset consists of Bank of Italy reports that indicate, for each bank, the number of bank branches across regions as well as its headquarters location. I use this information to sort banks across Italian regions, which allows me to exploit within-region banks' heterogeneity across sovereign exposure.

The main challenge is to isolate the bank-lending channel from other (demand-driven) factors that may affect corporate NPLs. For instance, banks with higher pre-crisis sovereign exposures may have been lending to riskier firms, or to industries or regions that were more affected during the crisis. To control for these factors, the literature (Bottero et al., 2020; Farinha et al., 2019; Bentolila et al., 2018; Bofondi et al., 2018; Buera and Karmakar, 2021; and Cingano et al., 2016) follows a Khwaja and Mian (2008) type of methodology and runs within-firm difference-in-difference regressions. They focus on firms with two or more banking relations and explore the differential effect on the loans supplied to the same firm across banks with different sovereign exposure.

That type of study is out of the scope of this paper. Instead, the analysis relies on a

[21] Appendix B.1 describes all of the variables used in the analysis.

simpler difference-in-difference framework that exploits within-region banks' heterogeneity. This allows me to capture all the demand-driven factors that operate at the regional level and that may be behind the increase in NPLs. Due to these limitations, the estimates in this section may not be interpreted as causal estimates. Nevertheless, they are still useful, because they provide evidence on the role of banks in the transmission 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. Appendix B.2 discusses these points in more detail.

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.[22] 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. To this end, I consider the following specification:

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

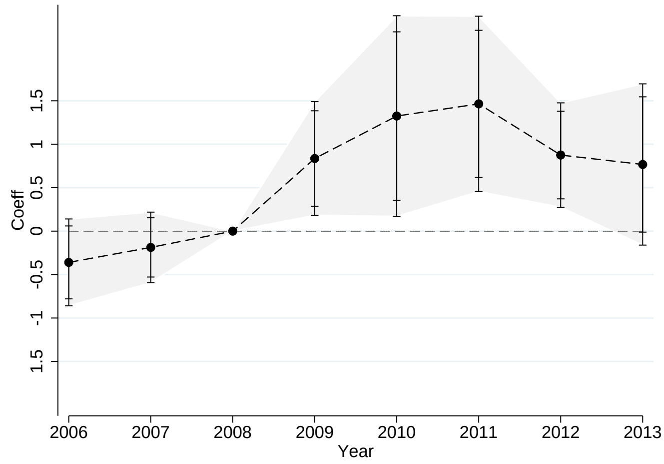
where $\Delta logNPLS_{i,j,(2008+h)}$ measures the change in nonfinancial NPLs (in logs) for bank i, located in region j, between the base year (2008) and horizon h. The variable $SovExp_{i,j,2008}$ measures bank i's holdings of sovereign debt at the base year; $X_{i,j,2008}$ is a vector of bank controls; and γ_j are region fixed effects. The set of controls includes bank size (as measured by log assets), loans, the share of loans to nonfinancial firms, liquid assets, retail funding, net worth, profits, and reserves. The coefficient of interest, $\beta_{1,h}$, measures the semi-elasticity of corporate NPLs to a bank's exposure to sovereign risk.

Results

Figure 3.6 shows the point estimates and confidence intervals for the $\beta_{1,h}$ coefficient for different horizons h. Before 2009, there are no significant differences in the growth rate of corporate NPLs for banks with different sovereign exposures. During the 2009-2012 period, the results show a positive and significant relation between the (pre-crisis)

[22] The 5 largest Italian banks are dropped, because these banks operate across all Italian regions. See Appendix B.1 for details.

Figure 3.6: Sovereign Exposure and Nonfinancial NPLs



Notes: The figure reports OLS estimates for the $\beta_{1,h}$ coefficients 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 nonfinancial nonperforming 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% 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 nonfinancial firms, liquid assets, retail funding, net worth, profits, and reserves. Annual frequency. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks.

sovereign exposure and the NPLs' growth rate. The estimated coefficients imply that a 1-standard-deviation increase in sovereign exposure is associated with a 15 pp increase in the growth rate of NPLs. Appendix B.3 provides additional tests to assess 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, within-region sovereign exposure is associated with a larger increase in counterparty corporate risk (as measured by corporate nonperforming loans). The analysis, therefore, highlights an important role of the bank-lending channel in the transmission of sovereign risk to the nonfinancial sector. In the next section, I employ the calibrated quantitative model to formally disentangle the transmission of sovereign to corporate risk through domestic banks.

4 Quantitative Analysis

4.1 Numerical Solution

The model described in Section 2 features heterogeneous firms, aggregate uncertainty, and important nonlinearities. At the firm level, the nonlinearities arise from the firms' default choice, while at the aggregate level they arise from the banks' occasionally binding leverage constraint. 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 (2.17) and (2.18), it is clear that the distribution of firms affects the demand for loans—and therefore the banks' stochastic discount factor—which implies that firms need to predict the evolution of this distribution to make their optimal choices regarding investment and debt issuance. To reduce the dimensionality, I follow the bounded-rationality approach of Krusell and Smith (1998) and use a finite set of moments that summarizes the firms' distribution. I solve the model using global methods and use graphic processing units (GPUs) to highly parallelize the algorithm (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 nonstochastic 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 1 quarter. Tables 4.1 and 4.2 summarize the values for all model parameters.

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 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.[23] 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).

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

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).[24] The discount factor β targets the median profits-to-capital ratio, since it governs the firms' desire to accumulate capital. I calibrate capital an debt adjustment costs to match the within-firm volatility of investment and leverage, respectively.[25] 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 σ_d to match the average corporate risk (as implied by Merton's distance to default) and the average corporate loan spread for nonfinancial Italian firms.[26]

Parameters for the Banks' and Government's Problems. With respect to the parameters governing the banks' problem, I fix the discount factor $\tilde{\beta}$, the survival rate ψ, 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%.[27]

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.[28] The probability of exiting a sovereign default ς_e 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 is calibrated to match an average maturity for Italian sovereign bonds of 80 months,

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

[25] I consider convex adjustment costs for both capital and debt. In particular, I assume the following specifications: $\Psi_k(.) \equiv \frac{\psi_k}{2}\left(\frac{k'-(1-\delta)k}{k}\right)^2 k$ and $\Psi_b(.) \equiv \frac{\psi_b}{2} \times \left(\frac{b'}{k'} - \frac{b}{k}\right)^2 \times k$, respectively.

[26] The target for corporate loan spreads is based on the entire universe of nonfinancial Italian firms. Corporate spreads are computed as the difference between bank lending rates to nonfinancial corporations (as reported by the Bank of Italy) and the short-term Euro repo rate (reported by the ECB).

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

[28] To closely follow the model-implied measure of leverage, I compute a bank's leverage as the ratio of its sovereign bond holdings plus corporate loans relative to its net worth.

Table 4.1: Calibration - Firm 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	Depreciation
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
σ_d	Exit Value (stdev)	1.80	Credit spreads & Default risk

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

as reported by the Italian Treasury Department. Also, c_G is set to match the debt services of the Italian government.[29] The parameter Δ_d targets an average recovery value of 50%, which is toward the upper end of the values used in the literature. Lastly, for computational tractability, I assume that the fiscal rule of Equation (2.9) 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 the government's bonds to nonfinancial loans in the balance sheet of Italian banks.[30]

Finally, the aggregate productivity loss in the event of a sovereign default ζ_D is internally calibrated to match the on-impact transmission of sovereign to corporate risk (from Section 3). To this end, I compute Merton's distance to default and 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%.

[29] 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.

[30] The assumption is for computational tractability since it allows me to decrease the dimensionality of the state space. As transfers are lump-sum; alternative fiscal rules have small aggregate implications.

Table 4.2: 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
ς_e	Prob. Exit Default	0.10	Default duration
m_G	1/Maturity	0.0375	Debt 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
ζ_D	Aggregate Default Cost	0.90	Empirical estimate

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

4.3 Targeted and Untargeted Moments

In this section, I assess whether the model can accurately approximate both the targeted moments and selected untargeted moments. I start with a description of moments for the nonstochastic 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 the) risk-free rate). I then describe moments for the case with aggregate risk and financial frictions.

Nonstochastic Steady State

Table 4.3 summarizes all of the targeted moments for the nonstochastic steady state. Overall, the model does a great job of approximating these 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 nonfinancial default risk and loan spreads.

Figure 4.1 compares the model-implied firm distribution with its empirical counterpart. The model does a good job of matching the distribution of firms in terms of size (Panel a) and, most importantly, in terms of risk (Panel b). For the majority of the Italian firms, (pre-crisis) corporate risk is below 1% and the model is able to match this

Table 4.3: Nonstochastic Steady State - Targeted Moments

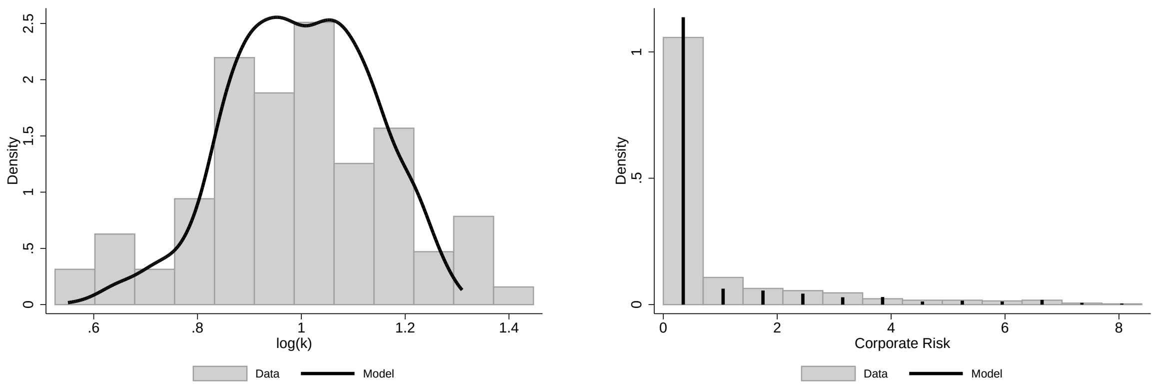
Targeted Moments (Steady State)	Data	Model
$log(k)$: 25th/50th percentile	0.879	0.867
$log(k)$: 75th/50th percentile	1.136	1.132
Quarterly Profits-to-Capital	0.093	0.104
Leverage (stdev)	0.078	0.074
Investment (stdev)	0.300	0.231
Firms' Recovery Rate	23%	21%
Corporate Risk (mean)	1.84%	1.94%
Firms' Spreads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

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

Figure 4.1: Nonstochastic 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 in 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 were retrieved from Datastream. Panel (b) shows the distribution of firms by risk. In both the model and the data, corporate risk is given by Merton's corporate-risk measure. The panel excludes firms with a default risk higher than 8%. Distributions for the Italian data are based on 2009.

Table 4.4: Economy with Sovereign Risk - Targeted and Untargeted Moments

Targeted Moments	Data	Model
Gov. Recovery Rate	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%
$\rho\left(SovRisk_{t-1}, GDP_t\right)$	-0.68	-0.48
$\rho\left(SovRisk_{t-1}, BankLeverage_t\right)$	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.

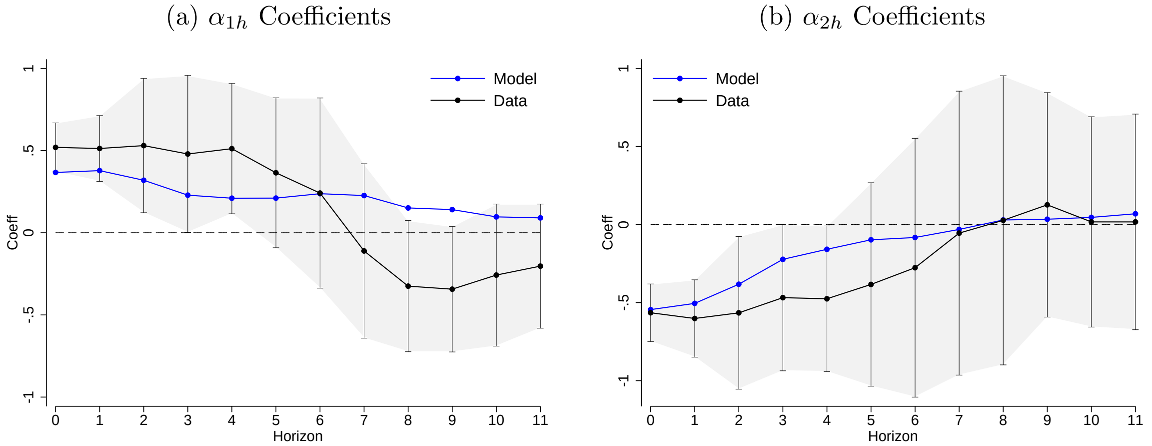
feature of the data. As shown in Section 3, firms with higher pre-crisis levels of corporate risk are the ones most affected by the sovereign debt crisis. Matching the risk distribution observed in the data is therefore crucial to understand the role of these riskier firms in amplifying the effects of the crisis.

Economy with Aggregate Risk and Financial Frictions

For the economy with aggregate uncertainty and financial frictions, the top panel of Table 4.4 compares the targeted moments for the government's recovery rate, banks' leverage, and banks' share of government bonds. The last row shows that the model matches the empirical estimate for the transmission of sovereign to corporate risk (from Section 3). Most importantly, as shown in Figure 4.2, the model not only matches the transmission on impact (which is a targeted moment), but also its persistence. In addition, the model is able to capture the asymmetric transmission of sovereign risk documented in the empirical analysis. As in the data, riskier firms are significantly more affected by changes in sovereign risk.

The bottom panel of Table 4.4 shows that the model can also approximate several untargeted moments, for instance, the average corporate leverage and the volatilities of aggregate output and investment. Lastly, the model-implied correlations between sovereign risk and output and between sovereign risk and banks' leverage are in line with those observed in the data, albeit smaller in magnitude. This is because the model abstracts from any spillover effect from the economy's fundamentals to sovereign risk.

Figure 4.2: IV Coefficients, by Firms with Different Risk - Model vs Data



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. In all simulations, the government never defaults. 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.

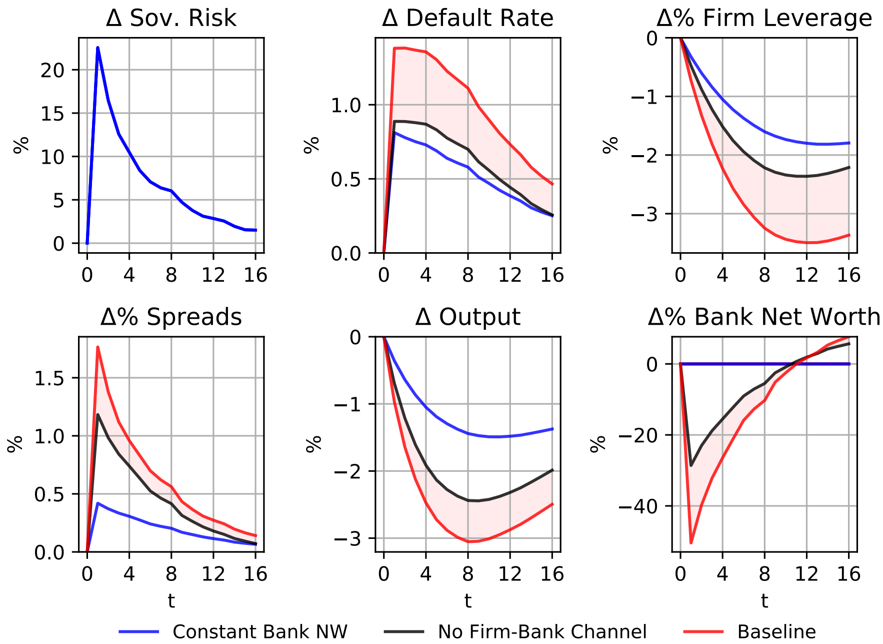
4.4 Decomposing the Effects and Role of Firm Heterogeneity

Figure 4.3 presents several counterfactuals to disentangle the different mechanisms at play. It shows the impulse response of five key variables to a 3-standard-deviation increase in sovereign risk. The blue lines show a counterfactual in which banks' net worth and leverage are constant. Under this counterfactual, changes in either sovereign or corporate risk have no effect on the credit supply. Thus, all of the effects are exogenous and explained by the firms' expected future productivity loss in the event of a sovereign default.

The black line shows a counterfactual in which changes in corporate risk do not affect banks' net worth or leverage. Under this scenario, the supply of credit is only a function of changes in sovereign risk. This counterfactual thus captures the main mechanism of the literature on the pass-through of sovereign risk (for instance, Arellano et al., 2019 and Bocola, 2016). In line with this literature, the results in Figure 4.3 show that changes in sovereign risk have a significant impact on banks' valuation, the supply of credit, and aggregate output.

Lastly, the red lines show the impulse response for the baseline model. In this case,

Figure 4.3: Decomposition of the Effects



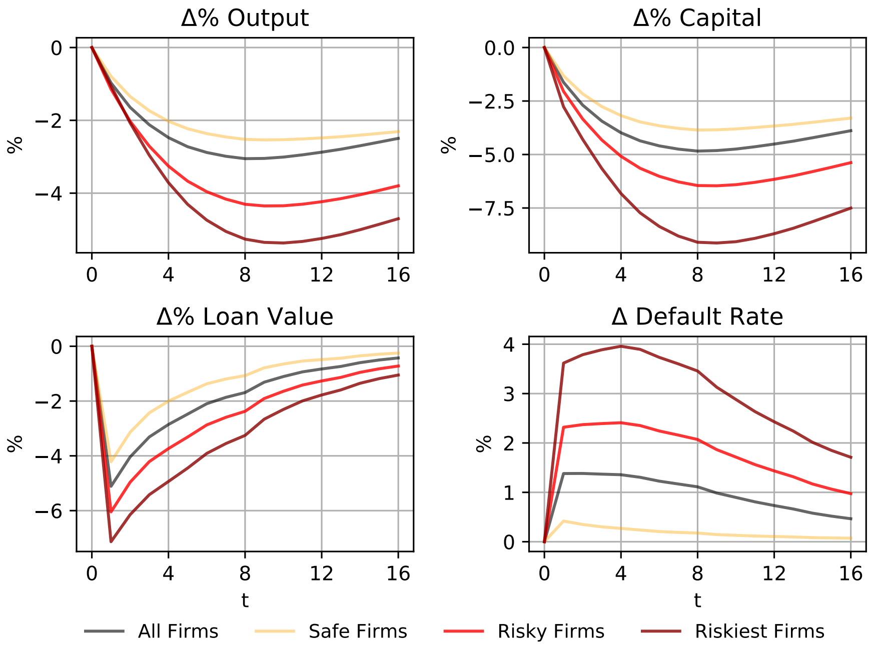
Notes: The figure shows the impulse response to a 3-standard-deviation increase in sovereign risk. Red lines show the results for the baseline model. Blue lines correspond to a counterfactual in which banks' net worth and leverage are constant. Black lines show a counterfactual in which changes in corporate risk do not affect banks' net worth. In all simulations, the government never defaults.

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 amplifying effects that arise due to this doom loop. Notice that (i) the firms' default rate (and corporate risk) increases significantly more, (ii) corporate risk contributes to almost half of the drop in banks' net worth, and (iii) the doom loop amplifies the drop in output by an additional 25%.

Taken together, these results show that through its effects on banks' balance sheets, corporate risk significantly amplifies a sovereign debt crisis. Despite its quantitative importance, the literature has been silent so far on this amplification mechanism.

What is the role of firm heterogeneity in the previous results? Figure 4.4 plots the same impulse response across firms with different levels of default risk (measured before the shock). The top panel shows that riskier firms reduce their output and stock of capital significantly more than the average firm, which is in line with the empirical estimates (see Appendix Figure A.3). In line with the results presented in Figure 4.2, the sovereign shock leads to a sharp increase in the default rates of high-risk firms but it does not change the

Figure 4.4: Heterogeneous Dynamics



Notes: The figure shows the impulse response to a 3-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 simulations, the government never defaults.

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 their default probability), the value of their loans decreases on impact almost twice as much compared with 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' balance sheets directly, the additional decrease in banks' net worth shown in Figure 4.3 (i.e., the red area) is thus mainly driven by higher-risk firms.

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, which amplifies 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 increases in sovereign risk.

4.5 Breaking the Amplification Mechanism

I study different policies that can dampen the negative effects of increases in corporate risk during a sovereign debt crisis. The first policy is a one-time capital injection into domestic banks. The second is a homogeneous debt-relief program across nonfinancial firms. The third is a heterogeneous debt-relief program for riskier nonfinancial firms (those with a default probability larger than 3%). All of these policies have the same fiscal cost (0.25% of quarterly GDP) and are financed through lump-sum taxes. Given that sovereign risk is exogenous, the analysis is silent on the effects of these policies on the government's default risk. For this reason, the goal is simply to quantify, for a given fiscal cost, which of these policies deliver a smaller contraction in output.

Appendix Figure C.2 shows that the capital injection to banks and the homogeneous debt-relief program do not have a large impact on firms' default rates and lead to similar dynamics in terms of aggregate output. In contrast, the heterogeneous debt-relief program leads to a much larger decline in default rates and to a smaller contraction of output. The heterogeneous debt-relief policy displays efficiency gains because it achieves two goals at the same time. On the one hand, it directly helps those firms that are financially constrained and closer to their default boundary, which allows for a smaller contraction in their output and investment levels. On the other hand, by lowering aggregate corporate risk, this policy indirectly recapitalizes the domestic banks, which benefits all firms (even safer firms) through its effects on the credit supply. Appendix Figure C.3 shows the effects of the heterogeneous debt-relief policy across firms with different levels of risk. The figure depicts important spillover effects that operate through banks and benefit firms that are not directly targeted by the policy.

5 Conclusion

I present a framework to study the macroeconomic implications of corporate risk during sovereign debt crises. I formulate a heterogeneous-firms model in which nonfinancial firms endogenously default on their long-term loans. Credit is provided by domestic banks, which are exposed to both sovereign and corporate risk. Increases in either sovereign or corporate risk hurt banks' lending capacity, which affects 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 corporate risk. Quantifying this transmission is thus crucial in order to assess the relative importance of the doom loop and, more generally, to quantify the aggregate implications of increases in corporate risk during a sovereign debt crisis.

I use Italian firm-level data to estimate the transmission of sovereign risk to nonfinancial firms 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 nonfinancial firms. The effects are quite persistent, lasting about 5 quarters, and can account for about 50% of the observed increase in Italian corporate risk. In addition, I find that there is a large heterogeneity across firms in this transmission. Safer firms, firms with lower leverage, and firms with a larger share of liquid assets are significantly less affected by changes in sovereign risk.

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. I show that the effects of corporate risk can be as pervasive as the effects of sovereign risk. In particular, I find that corporate risk can account for almost half of the drop in banks' net worth and that through its effects on banks' balance sheets, it amplifies the drop in output by more than 25%. I also show that policies that directly target riskier nonfinancial firms are more effective in breaking this doom loop.

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For Online Publication: Appendix for The Asymmetric Pass-Through of Sovereign Risk, by Matías Moretti

A The Transmission of Sovereign to Corporate Risk: Additional Material

A.1 Data Sources and Description of Variables

This section describes the variables used in Section 3. I use Compustat Global to retrieve quarterly balance-sheet data for publicly traded nonfinancial Italian firms. The variables used are *assets total (ATQ)*, *long-term liabilities total (LLTQ)*, *current liabilities total (LCTQ)*, *net sales (SALEQ)*, and *cash and short-term investments (CHEQ)*. The dataset covers around 300 firms during the 2004-2017 period although not all of the firms report consistently. I use log assets to proxy for a firm's size. As in Gilchrist and Zakrajšek (2012), to control for differences in a firm's maturity structure, I define liabilities as the sum of a firm's current liabilities plus half of its long-term liabilities. Leverage is defined as the ratio between liabilities and total assets. Table A.1 provides summary statistics for the 2009.Q2 period.

I use Bloomberg for daily data on the stock prices and shares outstanding for each firm. I combine these two datasets to compute Merton's distance to default (see Appendix A.2). In order to compute the distance to default, I include firms that were active (at least) during the entire 2007-2013 period. I exclude from the analysis firms with an average default probability larger than 25%. These criteria reduce the number of firms to around 150 firms. Lastly, I use Datastream to obtain daily data on the 10-year Italian government CDS spreads, the S&P 500, and the VIX.

A.2 Merton's Distance-to-Default Framework

To measure nonfinancial 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, they can be inferred from the value and volatility of the firm's equity and debt.

The Merton model makes two key assumptions. The first is that the value of a firm

Table A.1: Nonfinancial Italian Firms - Summary Statistics

Variable	Mean	Stdev	Pc10	Pc50	Pc90
log Assets	5.880	1.804	3.804	5.692	8.390
Long-term Liabilities/Assets	0.239	0.144	0.062	0.212	0.431
Current Liabilities/Assets	0.420	0.206	0.179	0.395	0.694
Leverage	0.537	0.197	0.298	0.513	0.748
Sales/Assets	0.182	0.102	0.067	0.166	0.309
Cash/Assets	0.092	0.113	0.017	0.056	0.179
Distance to Default	3.474	2.159	1.266	3.100	6.300
Corporate Risk	3.993	10.555	0.000	0.138	10.467

Notes: The table shows descriptive statistics for the panel of publicly traded nonfinancial Italian firms from Compustat Global. Variables are measured at the end of 2009.Q2.

(V) follows a geometric Brownian motion given by

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

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 is that the firm has issued only one discount bond that matures 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 firm's debt (D).

From Black-Scholes-Merton option-pricing model, a firm's equity value is

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

where $\delta_1 \equiv \frac{1}{\sigma_V\sqrt{T}}\left(log(V/D) + (r + 0.5\sigma_V^2)T\right)$, $\delta_2 \equiv \delta_1 - \sigma_V\sqrt{T}$, $\Phi(.)$ 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

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

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. Lastly, σ_E can be estimated using historical returns data. Using $\{D, E, \sigma_E\}$, we can then solve Equations (A.2) and (A.3) to map these observed variables into the unobserved components V and σ_V.[31] After we solve for these two variables, the distance

[31] As shown by Vassalou and Xing (2004), market leverage V/E typically displays a large degree of

to default can be computed as

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

Under this framework, default occurs whenever $V/D < 1$. Merton's dd can therefore be interpreted as the number of standard deviations by which 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.3 Financial and Trade Links between Italy and Greece and Portugal

This appendix describes the trade and financial linkages between Italy and Greece and Portugal. Using the European Banking Authority (EBA) 2011 Stress Test dataset, Table A.2 shows the sovereign risk exposure for 5 of the largest Italian banks to other European countries. Their exposure to Greece and Portugal is almost negligible, since it represents less than 0.7% of their entire sovereign exposure (which implies less than 0.1% of their assets). In fact, Italian banks are 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 debt holdings. Table A.3 shows that Greek and Portuguese banks are not significantly lending to Italian firms. Lastly, Table A.4 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.

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.

Table A.2: Sovereign Risk 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 debt holdings by country for 5 Italian banks as a share of their total sovereign debt holdings. 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 in percentage points. Source: European Banking Authority 2011 Stress Test.

Table A.3: Total Exposure by Country - European Banks

	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 are expressed as a fraction of the total EAD by banks' domicile (in percentage points). Source: European Banking Authority 2011 Stress Test.

Table A.4: 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. Values correspond to 2009. Results expressed in percentage points. The GIIPS (ex ITA) row includes exports (imports) to (from) Greece, Portugal, Spain, and Ireland. Source: OECD.

A.4 Additional Results and Robustness

This section presents additional results for the analysis in Section 3. Table A.5 shows some summary statistics for the ξ_t sovereign risk shock. Panel A shows moments for ξ_t aggregated at a daily frequency and Panel B reports them at a quarterly frequency.

Table A.6 presents the details of the baseline estimates reported in Figures 3.3 and 3.4. The table reports the estimates for horizon $h = 0$. The table also shows the interaction coefficients capturing the asymmetric transmission of sovereign risk (i.e., α_{20}) after including time fixed effects. For completeness, Figure A.1 reports the estimates for α_{2h} (for different horizons h) after including time fixed effects. The estimates are still significant and in line with those presented in the main text.

Figure A.2 shows that the sovereign risk shock at time t, ξ_t, is not related to changes in corporate risk at a previous time. The figure considers an identical specification to the one of Equation (3.1) and shows that both α_{1h} and α_{2h} are not significant (at the 0.05 level) for any $h < 0$.

To analyze the real implications of the transmission of sovereign risk to nonfinancial firms, I analyze how a firm's investment is affected by changes in sovereign risk. In particular, I consider the following 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 assets as a proxy for its investment given that variables referring to a firm's stock

Table A.5: Italian Reaction to Foreign News Events

Panel A. Daily Frequency	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

Panel B. Quarterly Frequency	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

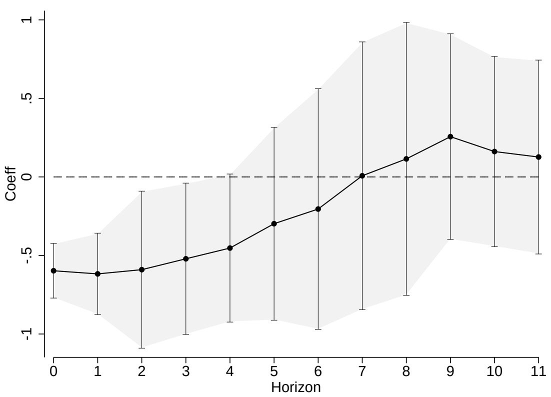
Notes: The table reports the reaction of Italian spreads around foreign news events. Events are based on Bahaj (2020) and are aggregated at the daily frequency (Panel A) and at the quarterly frequency (Panel B). Italian spreads are computed as the difference between the 10-year Italian government bond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

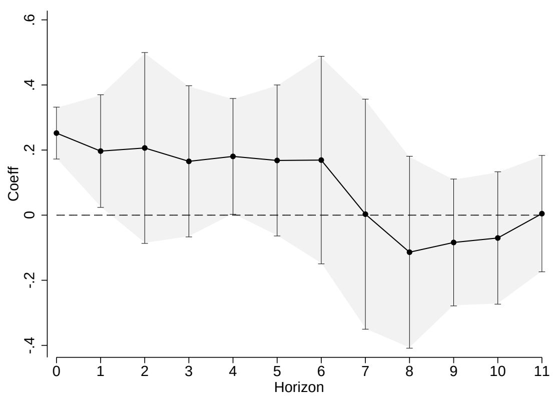
Table A.6: Asymmetric Transmission of Sovereign Risk - Details

	(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 on-impact response to sovereign risk shocks. The specification considered is $\Delta CR_{j,t} = \alpha_0 + \alpha_1 \xi_t + \alpha_2 [\xi_t \times a_{j,t-1}] + \alpha_3 Z_{j,t-1} + \gamma_j + \epsilon_{j,t}$. 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 of the specifications include firm fixed effects. Columns (3) and (6) further include quarter fixed effects. Quarterly frequency. Standard errors are clustered at the firm and quarter level.

Figure A.1: Asymmetric Transmission of Sovereign Risk; Including Time Fixed Effects





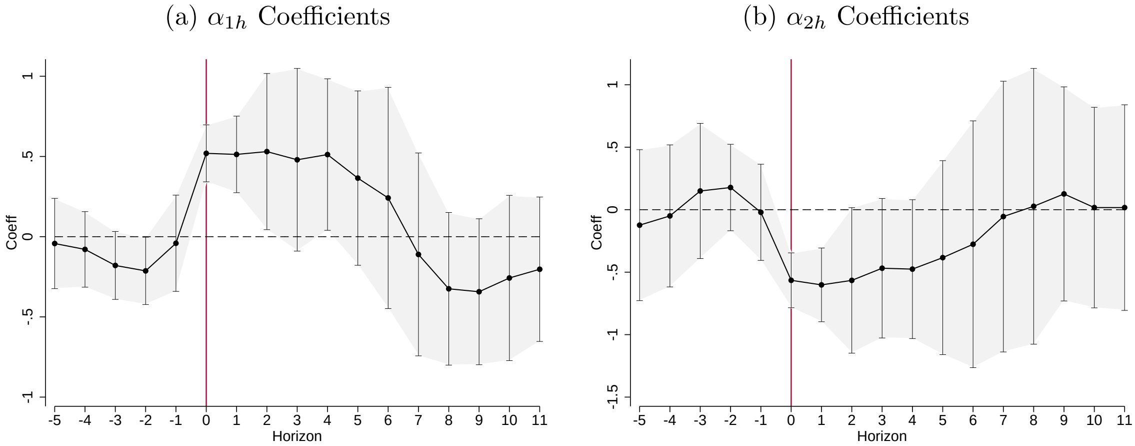
Notes: The figure shows the dynamics of heterogeneous responses to sovereign risk shocks. The specification considered is $\Delta CR_{j,t+h} = \alpha_{0h} + \alpha_{1h}\xi_t + \alpha_{2h}\left[\xi_t \times a_{j,t-1}\right] + \alpha_{3h}Z_{j,t-1} + \gamma_j + \Gamma_t + \epsilon_{j,t+h}$, where Γ_t are 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.

of capital (for instance, equipment, plant, and machinery) are inconsistently reported in the Compustat Global dataset. 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 this change depends on a firm's distance to default. The results are reported in Figure A.3. 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).

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.4 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 variables. Given 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 with respect to this specification is that the documented asymmetric transmission may be just capturing a proportional increase in risk across all

Figure A.2: Asymmetric Transmission of Sovereign Risk; Pre-Trend Analysis



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 95% confidence intervals. Standard errors are clustered at the firm and quarter level.

firms. In Figure A.5, I show that this is not the case. I consider the same local projection as in Equation (3.1) 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.

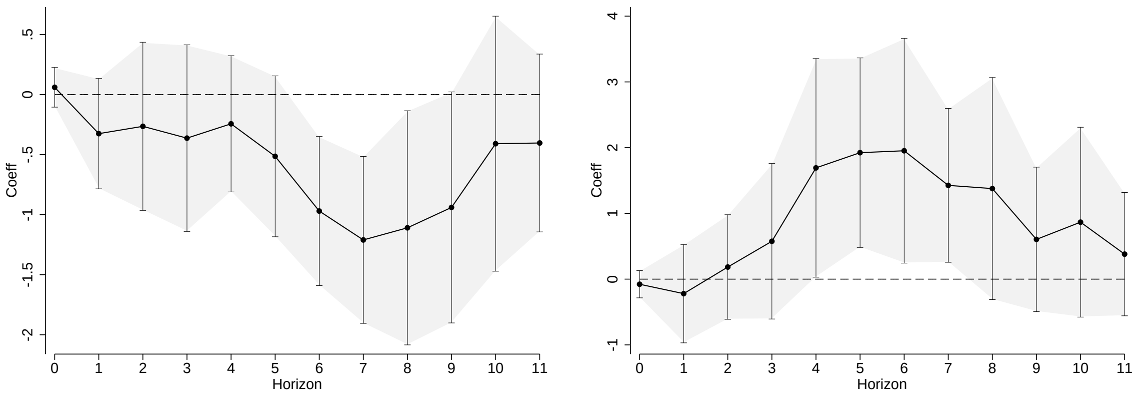
The results in the main text are also robust to alternative measures of corporate risk and frequency of the data. In Figure A.6, I consider the daily effect of a sovereign risk shock on Italian corporate bond spreads. In particular, I use the "Iboxx Corporates Italy," which is a daily index reflecting an average yield for a set of nonfinancial Italian firms. I then compute an average bond spread, $C\bar{R}_t$, 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 daily change in the Italian corporate bond spread, ξ_t is the sovereign risk shock, and X_t is a vector of global controls. Results are displayed in Figure A.6 (black lines). As a benchmark, I consider a similar specification to the one in Equation (A.6) but I use Merton's daily measure of corporate risk as the dependent variable. The estimates are all positive and significant, albeit slightly smaller for the case of corporate

Figure A.3: Asymmetric Transmission of Sovereign Risk; Investment Dynamics

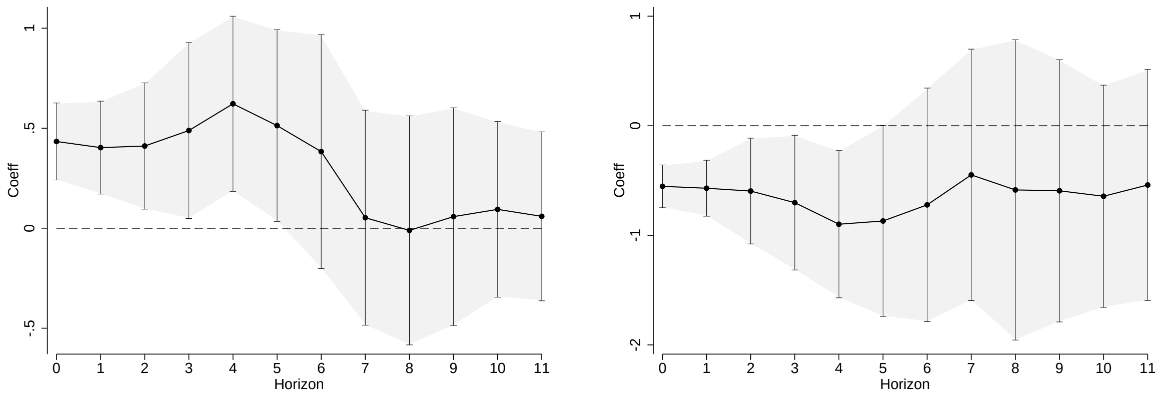
(a) α_{1h} Coefficients (b) α_{2h} Coefficients



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.

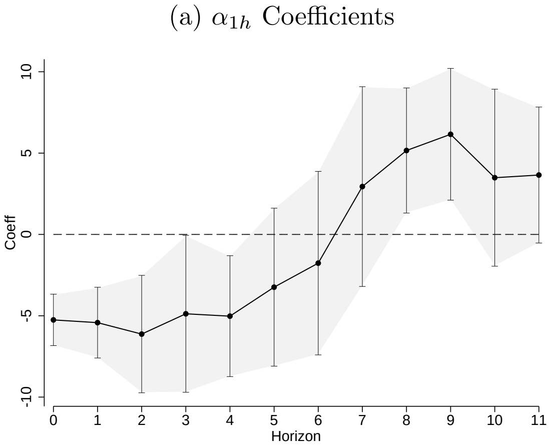
Figure A.4: Asymmetric Transmission of Sovereign Risk; Alternative Definition of Events

(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.5: Asymmetric Transmission of Sovereign Risk; Alternative Measures of Risk



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.

bond spreads.[32] As a comparison, the red lines show the estimates when the ξ_t shock is replaced with the daily change in the 10-year Italian CDS spread. As expected, the magnitude of those estimates is larger, given that they account for the feedback between corporate and sovereign risk.

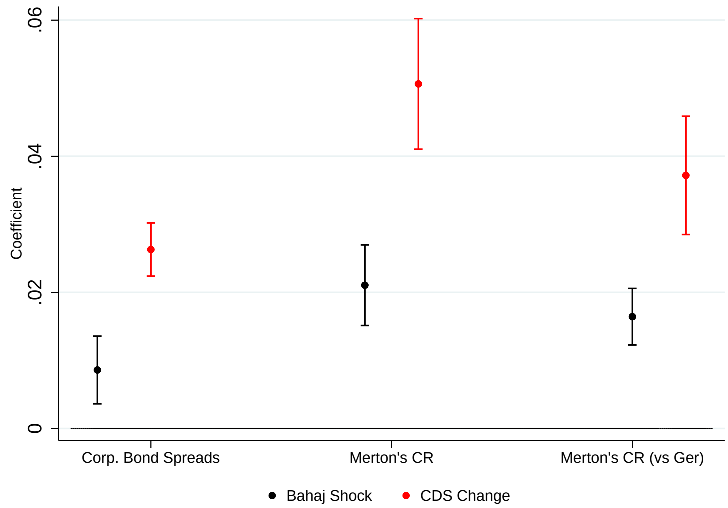
Figure 3.5 in the main text shows that the results are robust to using a set of German firms as a control group. To shed more light on the role of common factors across firms with different risk profiles, I sort firms across bins based on their pre-crisis risk profile. For each bin i, I consider the 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 ξ_t is the sovereign risk shock, $dd_{j,t-1}(i)$ is the distance to default of firm j that belongs to bin i, and X_t is a vector of global controls. Figure A.7 reports the $\alpha_1(i)$ estimates for the sample of Italian firms (Panel a) and German firms (Panel b). The point estimates across all of the considered bins are significantly smaller for German firms. Even the subset of riskiest German firms are almost unaffected by changes in ξ_t.

[32]The economic magnitudes are slightly smaller than those presented in the main text based on quarterly data. At the daily frequency, the standard deviation of ξ_t is 2.29 bps (taking into account days in which there are no news events and $\xi_t = 0$). Given that the total cumulative change in the ξ_t shock was about 120 bps, then the estimates of Figure A.6 account for about 20% of the total increase in corporate risk (as measured by Merton's distance to default).

Figure A.6: Comparison with Corporate Bond Spreads

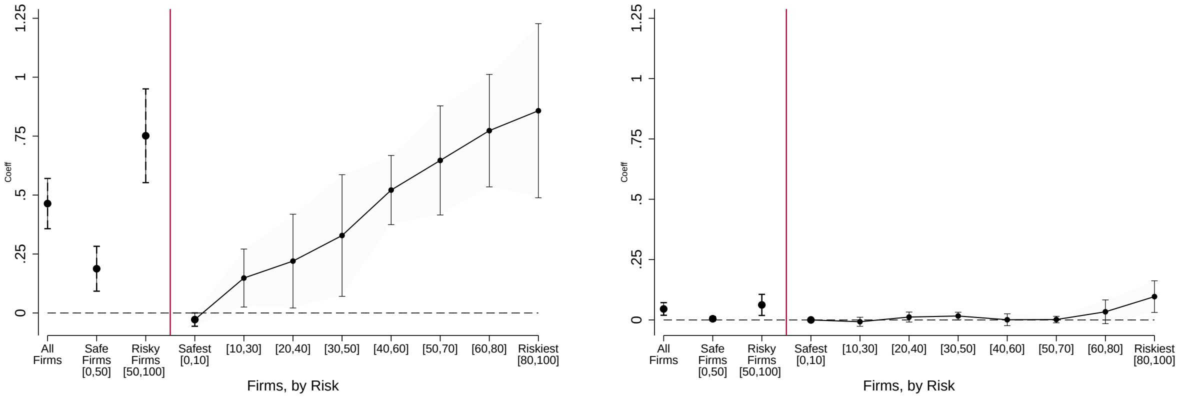


Notes: The figure shows the daily aggregate response to sovereign risk shocks. The black lines show the estimates for the following specification: $\Delta C\bar{R}_t = \bar{\alpha_0} + \bar{\alpha_1}\xi_t + X_t + \epsilon_{j,t+h}$, where the ξ_t shock is based on high-frequency market reactions to news from Greece and Portugal. The red lines show the estimates when the ξ_t shock 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 A.8 shows the α_1 estimates for different European countries (Italy, Spain, Germany, France, and Austria) for the case in which all firms are included. The estimates are large and significant for Italy and Spain, which are countries affected by the sovereign debt crisis. While smaller, the estimates are still significant for the other countries, which may suggest the presence of common shocks. Overall, the figure highlights the importance of controlling for German firms to purge these common factors.

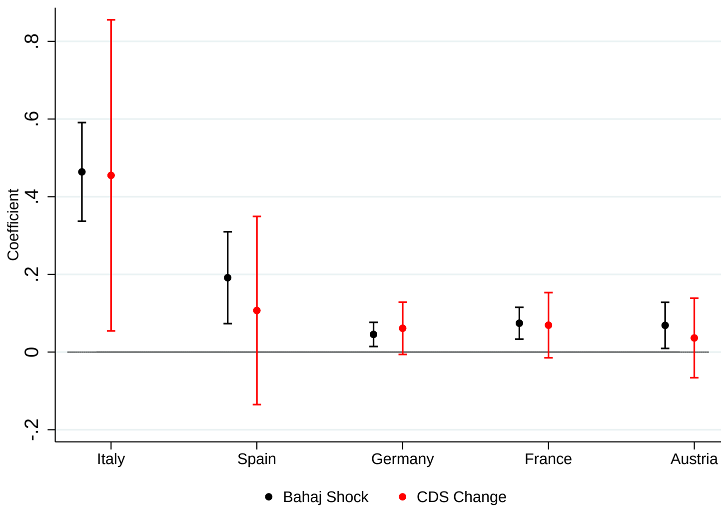
Figure A.7: Heterogeneous Effects, by Firm Risk

(a) Italian Firms (b) German Firms



Notes: The figure reports the heterogeneous responses to sovereign risk shocks. Firms are sorted across 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&P 500 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% confidence intervals. Standard errors are clustered at the firm and quarter level.

Figure A.8: 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 red lines, the ξ_t shock 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&P 500 and the VIX index. Quarterly frequency. Lines depict the 95% confidence intervals. Standard errors are clustered at the firm and quarter level.

B The Role of Banks: Additional Material

B.1 Data Sources and Description of Variables

This section describes the variables used in Section 3.4. 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.

I retrieve the following variables relative to a bank's assets: Total assets, risk-weighted assets, sovereign bond holdings, liquid assets (cash), total loans, loans to nonfinancial 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 nonfinancial sector relative to total loans. *NPLs* is defined as the sum of bad loans and substandard loans. *Non-Fin NPLS* is defined analogously but only loans to nonfinancial firms are included. I also extract the following variables regarding a bank's liabilities and net worth: Payables to customers, reserves, net worth, and operating profit (loss). 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 robustness analysis, I also obtain the following variables from the ABI dataset: Assets held for trading, assets for sale, payables to other banks, capital, and Tier1 ratio. Using this information, I then 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. It is thus not possible to quantify banks' direct exposure to Italian government bonds. However, as described in Table A.2,

Table B.1: Italian Banks - 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: The table shows descriptive statistics for the panel of Italian banks from the BilBank dataset. Sovereign exposure, loans, liquid assets, retail funding, net worth, profits, and reserves are expressed in terms of banks' (risk-weighted) assets. Nonperforming loans (NPLs) are expressed in terms of banks' loans. Loans to nonfinancial firms are expressed as a fraction of total banks' loans. Variables are measured at the end of 2008.

the EBA 2011 Stress Test shows that, for 5 of the largest Italian banks, holdings of Italian sovereign debt represent around 85% of their total sovereign exposure. For the analysis in Section 3.4, I assume that all sovereign exposures are in fact domestic exposures. Arellano et al. (2019), for instance, follow the same assumption. On this point, Kalemli-Ozcan et al. (2020) use detailed confidential ECB data and show that there is a strong home bias in sovereign debt 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 bond holdings exhibit a large home bias.

B.2 The Role of Firm-Level Factors

This section describes in more detail the limitations of the analysis presented in Section 3.4. As mentioned in the main text, to control for demand (firm-level) characteristics, the empirical literature (Buera and Karmakar, 2021; Bottero et al., 2020; Farinha et al., 2019; Bentolila et al., 2018; Bofondi et al., 2018; 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 this paper, since it requires loan-level data to match each firm with its lending bank. Instead, the analysis relies on a simpler difference-in-difference framework that exploits within-region heterogeneity across banks to capture all of the demand factors that operate at the regional level.

To capture these regional-level factors, banks are sorted across 20 Italian regions based on the domicile of their headquarters, as reported by the Bank of Italy.[33] If a bank reports more than one headquarters, it is classified based on the region in which the bank has more branches. 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. The 5 largest Italian banks (in terms of the assets reported in the ABI dataset) are dropped, since 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.

Regional Heterogeneity

Figure B.1 shows the importance of controlling for regional factors. Panel (a) shows banks' sovereign exposures and Panel (b) reports the 2009-2010 GDP change for each Italian region. At the regional level, there is a clear positive relation between sovereign exposure and the size of the recession. While part of the recession may have been driven by the larger exposure to sovereign risk, 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 highlights that it is important to control for regional-level factors.

Table B.2 provides a breakdown of the main variables of interest across the 5 Italian macro-regions: North-West (NW), North-East (NE), Center, South, and Islands.[34] The table shows an important degree of heterogeneity across regions. For instance, banks in the South region are typically smaller, with larger sovereign bond holdings and a higher ratio of nonperforming loans.

Identifying Assumptions and Interpretation of the Results

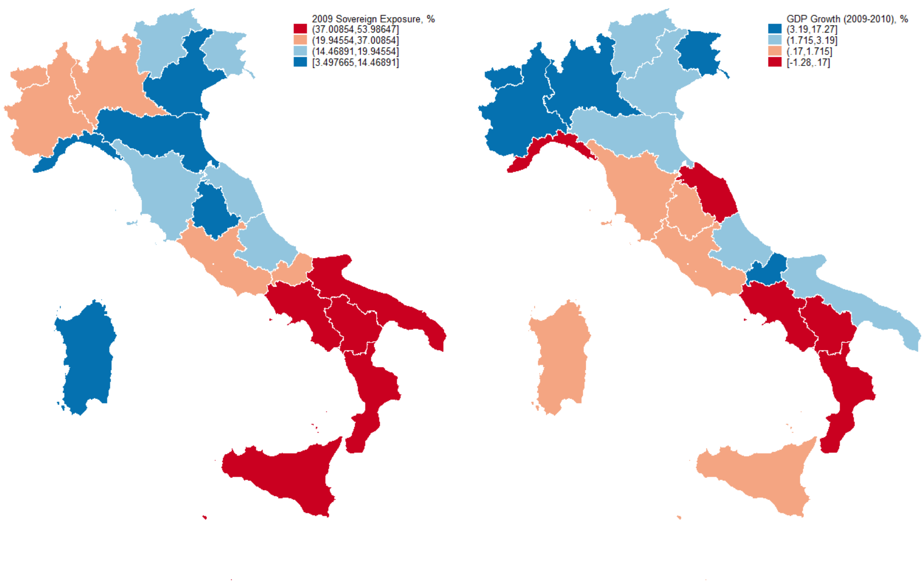
If the increase in NPLs is correlated with unobservable firm-specific conditions that also correlate with a bank's sovereign exposure, the OLS estimates for $\beta_{1,h}$ of Equation (3.2)

[33]The Italian regions are the following: 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. Results are similar if banks are sorted into regions based on the number of branches of each bank.

[34]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.

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

(a) Banks' Sovereign Risk Exposure (b) GDP Growth



Notes: The figure shows Italian banks' sovereign exposure (Panel a) and the 2009-2010 GDP growth rate (Panel b) by region. The 5 largest Italian banks are excluded. Each bank is sorted into each region based on the location of its headquarters.

would be biased. For instance, the estimates would be biased if banks with higher sovereign exposure were systematically lending to riskier firms or to firms that were more affected during the European debt crisis. The specification in (3.2) allows for unbiased estimates under three conditions:

(i) Unexpected Shock: At the end of the base year (i.e., 2008), Italian banks should not have anticipated the European debt crisis. If this were not the case, then banks could have adjusted the risk profile of their loans in anticipation of the crisis, creating a bias in the estimates for $\beta_{1,h}$. Buera and Karmakar (2021); Bottero et al. (2020); and Acharya and Steffen (2015), 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 a bank's loans. That is, if it were not for the sovereign debt crisis, banks with higher sovereign debt holdings should display an increase in NPLs similar to those banks with a 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, given that the estimates for $\beta_{1,h}$ are not statistically significant before the crisis.

(iii) Absence of firm-level factors: Given that the specification in Equation (3.2) does

Table B.2: Italian Banks - 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 (nonfinancial firms)	0.030	0.062	0.047	0.061	0.072

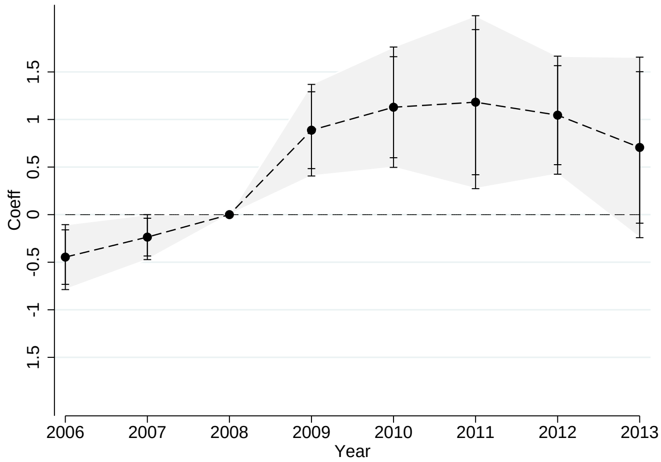
Notes: The table shows summary statistics at the regional level. Variables are measured at the end of 2008. Sovereign exposure is expressed in terms of banks' assets. Nonperforming loans are expressed in terms of banks' loans. Table reports averages across banks (except for branches, for which the sum is reported). The 5 largest Italian banks are excluded. Results are not weighted by bank size.

not control for firm-level factors, in order to provide unbiased estimates 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 the 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 is driven purely due to limitations of the dataset. In 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.*" Buera and Karmakar (2021); Farinha et al. (2019); 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 of the demand-level factors that influence NPLs, they are far from being a fully compelling argument. Due to these limitations, the estimates presented in Section 3.4 may not be

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



Notes: The figure reports OLS estimates for the $\beta_{1,h}$ coefficients 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 nonperforming loans, as reported by bank i located in region j. The measure of nonperforming loans includes both nonfinancial NPLs and NPLs of other banks' customers. The shaded area shows the 95% confidence interval (vertical lines display the 90% and 95% CI). Standard errors are clustered at the regional level. The set of controls includes bank size (as measured by log assets), loans, share of loans to nonfinancial firms, liquid assets, retail funding, net worth, profits, and reserves. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks.

interpreted as a causal estimate.

B.3 Additional Results

I provide additional results and tests for the analysis presented in Section 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 NPLs of both nonfinancial firms and other banks' customers. The results are in line with those presented in Figure (3.6), which suggests that the increase in default rates was not specific to the nonfinancial sector.

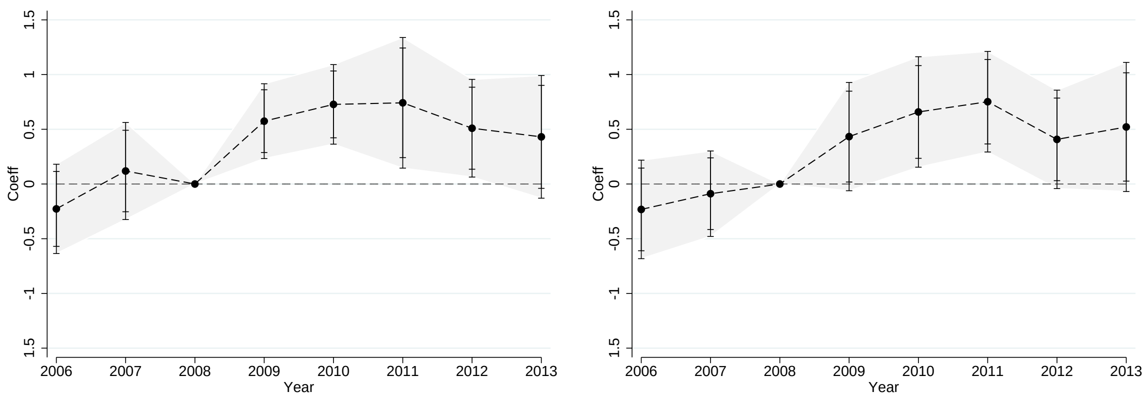
The results are robust to alternative specifications of the dependent variable. Figure B.3 shows the results when the dependent variable is defined as

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

This growth rate is bounded in the range $[-2, 2]$, which limits the influence of outliers. Buera and Karmakar (2021) and Bottero et al. (2020) use the same standardization. The estimated coefficients are in line with the ones presented in the main analysis (albeit

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

(a) All NPLs (b) Corporate NPLs



Notes: The figure reports OLS estimates for the $\beta_{1,h}$ coefficients in Equation (3.2). The dependent variable is $\%\Delta NPLs$, as defined in Equation (B.1). Panel (a) includes the entire stock of a bank's NPLs. Panel B includes NPLs of the nonfinancial sector only. The shaded area shows the 95% confidence interval (vertical lines display the 90% and 95% 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 Panel (b), the share of loans to nonfinancial firms is also included as a control. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks.

slightly smaller in magnitude). For the rest of this appendix, I consider $\%\Delta NPLS$ as the main dependent variable.

Table B.3 provides a further description of the estimates for the year 2011. Apart from the sovereign exposure, a bank's share of loans and its capital structure (in particular, its reserves) seem to be the main drivers behind changes in NPLs. Columns (1) and (4) show the results without region fixed effects. The magnitude of the estimates for $\beta_{1,h}$ are higher in these cases, given the regional-level correlation between sovereign exposures and GDP growth. Since a bank may be operating across different regions and not only in the region where its headquarters are located, columns (3) and (6) report the estimates for a broader level of aggregation. Instead of sorting banks across 20 Italian regions, each bank is sorted into one of the 5 Italian macro-regions (as defined in Table B.2). The estimates are in line with those associated to the finer level of aggregation. Figure B.4 reports the macro-region-level estimates for different horizons h. If anything, this level of aggregation displays a larger persistence in the estimated effects.

Figure B.5 presents the results when the dependent variable is measured as the ratio

Table B.3: Sovereign Exposure and NPLs - Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
		All NPLs			Nonfinancial 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. The dependent variable is $\%\Delta NPLs$, as defined in Equation (B.1). Sample excludes the 5 largest Italian banks. Columns (1) and (4) show the results without regional fixed effects. 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 regional 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.

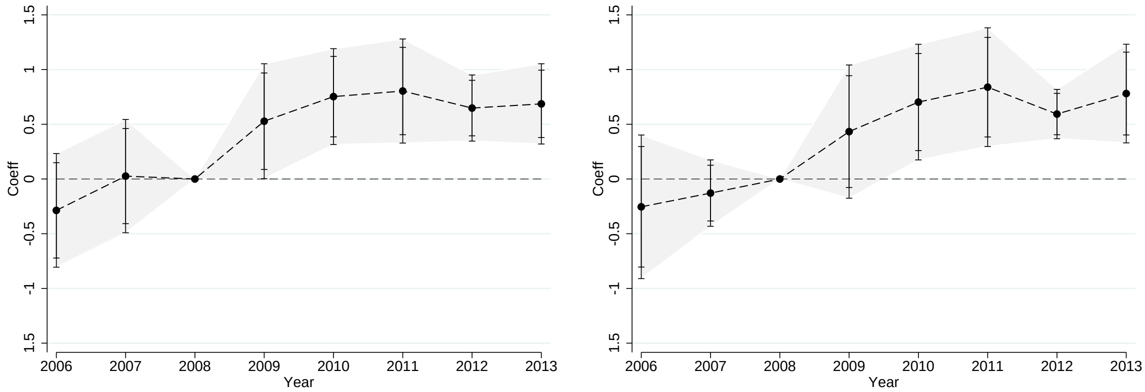
between NPLs and a bank's loans. That is

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

Arguably, this is a better measure of the change in a bank's portfolio quality as it measures the changes in NPLs relative to changes in a bank's loans. 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 magnitudes of the estimates in Figure B.5 are slightly larger than those in Figure B.3.

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

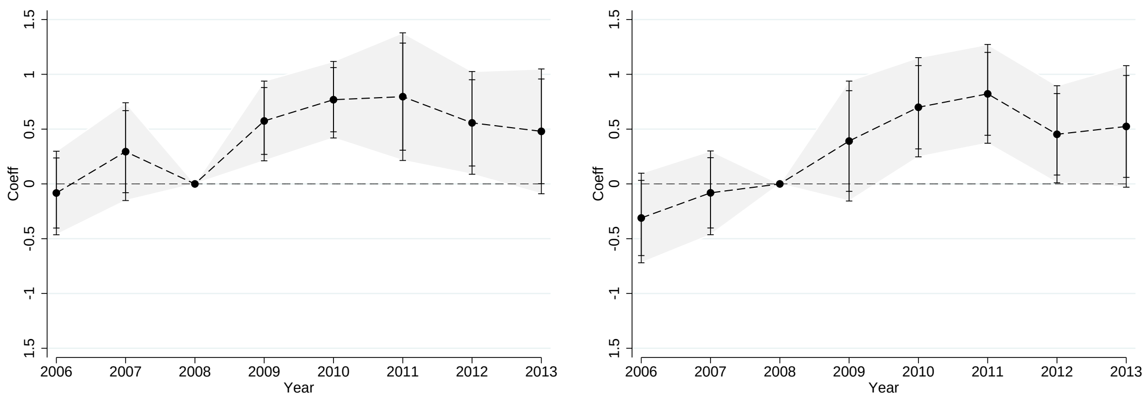
(a) All NPLs (b) Corporate NPLs



Notes: Figures report OLS estimates for the $\beta_{1,h}$ coefficients in Equation (3.2). The dependent variable is $\%\Delta NPLs_{i,j,h}$, as defined in Equation (B.1). Banks are sorted across the 5 Italian macro-regions: North-West, North-East, Central, South, and Islands. Panel (a) includes the entire stock of a bank's NPLs. Panel B includes NPLs of the nonfinancial sector only. The shaded area shows the 95% confidence interval (vertical lines display the 90% and 95% 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 Panel (b), the share of loans to nonfinancial firms is also included as a control. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks.

Figure B.5: Sovereign Exposure and NPLs - Dependent Variable: $\%\Delta\left(\frac{NPLS}{Loans}\right)$

(a) All NPLs (b) Corporate NPLs



Notes: The figure reports OLS estimates for the $\beta_{1,h}$ coefficients in Equation (3.2). The dependent variable is $\%\Delta NPLs/Loans$, as defined in Equation (B.2). Panel (a) includes the entire stock of a bank's NPLs. Panel B includes NPLs of the nonfinancial sector only. The shaded area shows the 95% confidence interval (vertical lines display the 90% and 95% 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 Panel (b), the share of loans to nonfinancial firms is also included as a control. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks.

Table B.4: Sovereign Exposure and NPLs - Additional Controls

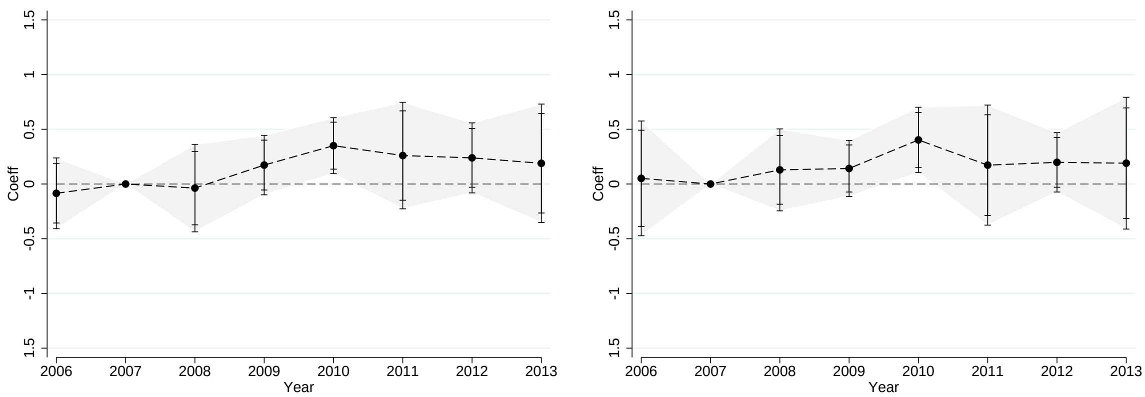
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sov Exposure	-0.1095	0.4457	0.4490	0.5197	0.7661	0.7520	0.7291	0.7223	0.7282	0.6827
	(0.3248)	(0.2606)	(0.2561)	(0.2558)	(0.2455)	(0.2345)	(0.2292)	(0.2403)	(0.2445)	(0.2385)
log(Assets)	0.0431	0.0603	0.0640	0.0530	0.0248	0.0187	0.0144	0.0074	0.0303	0.0195
	(0.0381)	(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
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports OLS estimates for the $\beta_{1,h}$ coefficients in Equation (3.2) for different specifications of the controls. Results are for the 2011 year only. The dependent variable is $\%\Delta NPLs$, as defined in Equation (B.1). Only NPLs of the nonfinancial sector are considered. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks. All of the specifications include region fixed effects. Standard errors are clustered at the regional level.

Figure B.6: Sovereign Exposure and NPLs - Alternative Base Year

(a) All NPLs

(b) Corporate NPLs



Notes: Figures report OLS estimates for the $\beta_{1,h}$ coefficients in Equation (3.2) but using 2007 (instead of 2008) as the base year. The dependent variable is $\%\Delta NPLs_{i,j,h}$, as defined in Equation (B.1). Panel (a) includes the entire stock of a bank's NPLs. Panel B includes NPLs of the nonfinancial sector only. The shaded area shows the 95% confidence interval (vertical lines display the 90% and 95% 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 Panel (b), the share of loans to nonfinancial firms is also included as a control. Sample includes all banks in the ABI dataset after excluding the 5 largest Italian banks.

Table B.4 reports the estimates for different sets of bank controls X_t and shows that the results are robust to different specifications (column 6 is the baseline specification). The estimates in columns (1)-(6) highlight the importance of controlling for relevant bank-level factors that may correlate with a bank's sovereign exposure and the risk profile of its 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 that describe a 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 securities holdings, bank funding, capital, and Tier 1. The results are robust to the addition of these other characteristics.

To provide further evidence that supports the parallel trend assumption, I repeat the main analysis with 2007 as the base year. The goal is to assess whether a bank's sovereign debt holdings in 2007 affect the growth rate of its NPLs during 2008, the year of the global financial crisis. This exercise allows me 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.6 show that the growth rate of NPLs during 2008 is not related to a bank's sovereign exposure in

2007, which provides evidence in favor of the parallel trend assumption. In other words, banks with higher sovereign risk exposure were not taking more corporate risk than their low exposure peers (after controlling for all of 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 suggest an important re-balancing of banks' portfolios after the 2008 crisis.

C The Quantitative Model: Additional Material

C.1 Characterization of Banks' Solution and Pricing Kernels

This section provides a proof for expressions (2.16)-(2.17) in the main text. The first step is to guess that the value function is a linear function of a 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 (2.15), we get

$$
\begin{aligned}
W(\eta, S) = {} & Max_{x', B', b'(.)}\ \tilde{\beta}\mathbb{E}\left[(1-\psi)\,\eta' + \psi\alpha(\boldsymbol{S'})\eta'\right] \\
& \text{s.t.} \\
& \quad \frac{1}{R_f(\boldsymbol{S})}x' + \eta = \int q\left(.,\boldsymbol{S}\right) b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B' \\
& \quad \eta' = -x' + \int \mathbb{R}_f(.,\boldsymbol{S'})b'(.,\boldsymbol{S})d\Omega + \mathbb{R}_G(\boldsymbol{S'})B' \\
& \quad \kappa\left(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B'\right) \leq \alpha(\boldsymbol{S})\eta \\
& \quad \boldsymbol{S'} = H\left(\boldsymbol{S}\right).
\end{aligned}
$$

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

$$
\begin{aligned}
W(\eta, S) = {} & Max_{B', b'(.)}\ \tilde{\beta}\mathbb{E}\left[\Lambda\left(\boldsymbol{S'}\right)\eta'\right] \qquad \text{(C.1)} \\
& \text{s.t.} \\
\eta' = {} & R_f\left(\boldsymbol{S}\right)\eta + \int \left[\mathbb{R}_f(.,\boldsymbol{S'}) - R_f\left(\boldsymbol{S}\right) q\left(.,\boldsymbol{S}\right)\right] b'(.,\boldsymbol{S})d\Omega + \left[\mathbb{R}_G(\boldsymbol{S'}) - R_f\left(\boldsymbol{S}\right) q_G\left(\boldsymbol{S}\right)\right] B' \\
\kappa & \left(\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B'\right) \leq \alpha(\boldsymbol{S})\eta \\
\boldsymbol{S'} = {} & H\left(\boldsymbol{S}\right).
\end{aligned}
$$

The first order conditions with respect to $b'(.,\boldsymbol{S})$ (for each firm) and B', and the slackness condition (assuming an interior solution for all of the variables) are given by

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

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

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

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

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

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

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

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

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

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

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

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

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

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 $q_G(\boldsymbol{S})$, we have

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

and

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

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

$$\Xi\left(\boldsymbol{S'},\boldsymbol{S}\right) \equiv \frac{\tilde{\beta}\Lambda(\boldsymbol{S}')}{\mu\left(\boldsymbol{S}\right)\kappa + \tilde{\beta}R_f\left(\boldsymbol{S}\right)\mathbb{E}\left[\Lambda(\boldsymbol{S}')\right]}. \tag{C.10}$$

Notice that the discount factor depends not only on whether the leverage constraint is currently binding or not but also on the 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 current SDF, since they affect the likelihood that the constraint may bind in the future. After replacing with the definition of the SDF and with the definitions of $\mathbb{R}_f(.,\boldsymbol{S})$ and $\mathbb{R}_G(\boldsymbol{S})$ provided in the main text, we can rewrite Equations (C.8) and (C.9) 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

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

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

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. 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 panel shows a strong correlation between changes in the Italian TFP and the government's risk-neutral default risk.[35] The right panel shows the *expected present value* (EPV) of future TFP paths. For each year t, this measure is given by

$$EPV_t(TFP) = \mathbb{E}_t \left[\sum_{i=0}^{\infty} \left(\frac{1}{1+r} \right)^i TFP_{t+i} \right], \tag{C.11}$$

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 line), which is a function of the sovereign risk process and the productivity loss ζ_D upon a sovereign default—see below for its derivation. Although 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 the expected aggregate productivity losses observed in Italy during the crisis.

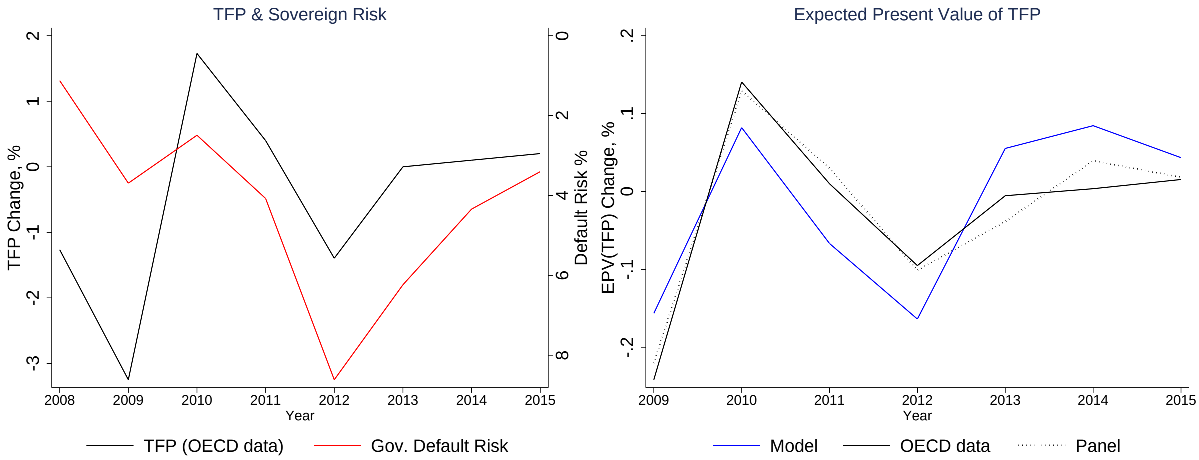
Computing the Expected Present Value (EPV) of TFP

To compute the empirical EPV, I assume the following AR(1) process for aggregate TFP:

$$log(TFP_{t+1}) = \alpha_0 + \alpha_1 log(TFP_t) + \sigma\epsilon_{t+1} \tag{C.12}$$

[35] 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 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 spreads. The right panel shows the expected present value (EPV) of TFP. The black solid line is based on the "Multi-factor Productivity" computed by the OECD. 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.

and estimate the coefficients $\{\alpha_0, \alpha_1, \sigma\}$ using Italian data.[36] Based on those estimates, I then 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 each year t, the EPV of TFP is computed as

$$E\tilde{P}V_t(TFP) = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=0}^{I}\left(\frac{1}{1+r}\right)^i TFP_{j,t+i}. \tag{C.13}$$

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, $\{s_t\}_{t=2008.q1}^{2015.q4}$.[37]

[36]For the Italian measure of TFP computed by the OECD, the estimates for $\{\alpha_0, \alpha_1, \sigma\}$ are based on data that cover the 1985-2015 period. I also estimate the aggregate TFP for the nonfinancial Italian firms used in the analysis of Section 3. For these firms, I first estimate an aggregate measure of TFP for the 2000-2015 period and then use those estimates as inputs in Equation (C.12). In the latter case, given the small length of the sample period, the results should be considered for illustrational purposes only.

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

As described in Section 2, this process follows an AR(1) process given by

$$s_{t+1} = (1-\rho_s)\, s^\star + \rho_s s_t + \sigma_s \epsilon^s_{t+1}. \tag{C.14}$$

Using Equation (C.14) and the calibrated parameters $\{\rho_s, \sigma_s, s^\star\}$, for each quarter t, I run $J = 10,000$ simulations of length $I = 1,000$ to construct $\{s_{j,t+l}\}_{j=1,i=0}^{J,I}$. 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

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

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

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

where ς_e is the (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

$$\zeta_t = \begin{cases} 1 & \text{if } h^G_t = 0 \\ \zeta_D & \text{if } h^G_t = 1. \end{cases}$$

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

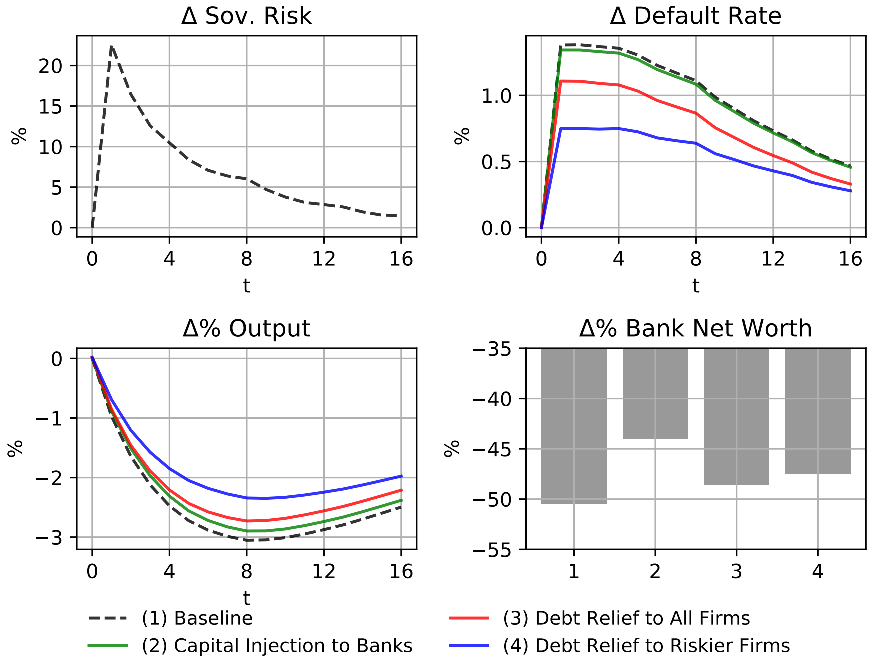
$$E\tilde{P}V_t(\zeta) = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=0}^{I}\left(\frac{1}{1+r}\right)^i \zeta_{j,t+i}. \tag{C.15}$$

C.3 Additional Figures

This section presents additional figures for the policy analysis in Section 4.5. Figure C.2 shows the aggregate implications for three different policies. The first is a policy in which the government directly injects capital into banks (green lines). I assume that at the time of the sovereign shock, the government makes a one-time capital injection equivalent to

$x\%$ of the banks' net worth. The second is a homogeneous debt-relief program across all firms (red lines). In this case, at the time of the shock, the government reduces the value of a firm's leverage by $y\%$, where y is chosen to match the fiscal cost of the previous policy. Lastly, I consider a policy that takes into consideration firms' heterogeneous reaction to sovereign risk (blue lines). In particular, I assume that at the time of the shock, the government reduces the leverage of a subset of "riskier firms" by $z\%$ and I choose z to match the same fiscal cost of the other policies. For illustrative purposes, I define "riskier firms" as those firms with an annualized default probability larger than 3%.

Figure C.2: Effects of the Policies

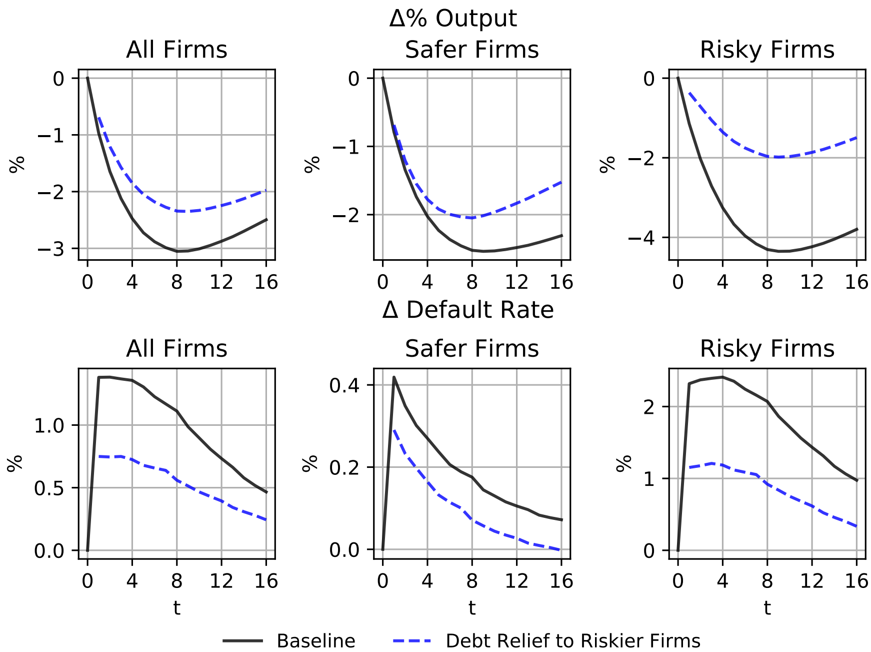


Notes: The figure shows the impulse response to a 3-standard-deviation increase in sovereign risk. It compares the baseline outcome (black dashed lines) with three different policies. Green lines show the results for a capital injection to banks. Red lines show the dynamics for the case in which the government runs a homogeneous debt-relief program across all firms. Blue lines show the dynamics for a debt-relief program for riskier firms (those with a default probability larger than 3%). The three policies have the same fiscal cost. In all simulations, the government never defaults. The bottom-right panel shows the change in banks' net worth on impact (at the time of the shock).

The capital injection to banks and the homogeneous debt-relief program do not have a large impact on firms' default rates and lead to similar dynamics in terms of aggregate output. In contrast, the debt-relief to riskier firms leads to a much larger decline in the aggregate default rate and further dampens the decline in output. This policy displays efficiency gains because it achieves two goals at the same time. First, it directly helps those firms that are financially constrained and closer to their default boundary, which dampens the contraction in their output and investment. Second, it reduces aggregate corporate risk, which leads to a smaller contraction in banks' net worth and benefits all firms through a larger credit supply. While the homogeneous debt-relief program also affects firms' default risk, a large share of the relief is designated towards safe firms which, before and after the shock, have small default probabilities. Thus, on average, the homogeneous debt-relief program has a smaller impact on aggregate corporate risk and banks' balance sheets.

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. The figure shows important spillover effects, given that safer firms that are not directly targeted by the policy also experience a smaller contraction in their output and a smaller increase in their default rates.

Figure C.3: Heterogeneous Debt-Relief Policy - Effects by Firms' Risk



Notes: The figure shows the impulse response to a 3-standard-deviation increase in sovereign risk. It compares the baseline outcome with a debt-relief program for riskier firms (those with a default probability larger than 3%). The black solid lines show the dynamics for the baseline model. The blue dashed lines show the dynamics for the debt-relief program. In all simulations, the government never defaults. Safe (risky) firms are those below (above) the 50th percentile in terms of firms' (pre-shock) default risk. The top panels show the percentage change in output. The bottom panels show the change in firms' default rate (annualized).

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 $\boldsymbol{S} \equiv (s, B, x, h_G, \Omega)$, where s denotes the exogenous sovereign risk process, B is the stock of government's debt, x are banks' deposits, h_G denotes the government's default status, and Ω denotes the firms' distribution across the three idiosyncratic states (k, b, z).[38]

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. Such distribution is a relevant variable for a firm's problem because of its implications on banks' stochastic discount factor and loan prices. From Equation (2.17) in the main text, notice that the Lagrange multiplier associated with a bank's leverage constraint is given by

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

From this expression it is clear that in order to predict current (and future) loan prices, firms need to predict the current (and future) ratio of banks' net worth to loans. Let $\Upsilon \equiv \frac{\eta}{\int q(.,\boldsymbol{S})b'(.,\boldsymbol{S})d\Omega + q_G(\boldsymbol{S})B'}$ denote the (end-of-period) inverse of banks' leverage. In equilibrium, to guarantee market clearing, firms' perceived value for Υ must also coincide with the observed value. Although Υ is not observed at the beginning of each period, to avoid inaccuracies that may arise from this perceived law of motion, I define Υ as an auxiliary aggregate variable in the firm's problem. Embedded inside Υ, we have relevant information describing firms' distribution across capital and leverage. Using Υ as a state variable has the advantage that the solution guarantees market clearing in each step of the simulation. Moreover, tracking Υ allows me to directly account for periods in which banks' leverage constraint is binding ($\mu(\boldsymbol{S}) > 0$).

Once Υ is included as a state variable, other moments summarizing the firm distribution are only relevant for forecasting Υ'. However, to keep the solution tractable, I

[38] 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 (while the government is not in default). The aggregate state can be written in terms of banks' deposits or in terms of their net worth (at the beginning of the period).

assume a forecasting rule independent of other moments of the firm distribution.[39] In particular, I consider the following state-contingent non-linear forecasting rule:

$$\tilde{H}\left(s, h_G, \Upsilon; s', h'_G\right) = \begin{cases} e^{a_0 + a_1 \Theta(s,s') + a_2 log(\Upsilon)} & \text{if } h_G = 0, h'_G = 0 \\ a_3 \Upsilon & \text{if } h_G = 0, h'_G = 1 \\ \Upsilon & \text{if } h_G = 1, \end{cases} \tag{C.16}$$

where $\Theta\left(s, s'\right)$ 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 $t+1$, I assume a proportional drop in Υ. Lastly, if the government is already in default, I consider a constant Υ.

Let $\tilde{\boldsymbol{S}} \equiv \left(s, h_G, \Upsilon\right)$ denote the aggregate state. Under these assumptions, a firm's recursive problem can be rewritten as

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

subject to

$$\begin{aligned} & d = \pi\left(k, z\right) - I\left(k', k\right) + q\left(., \tilde{\boldsymbol{S}}\right) \times \left[b' - \left(1 - m_f\right) b\right] - \left[\left(1 - m_f\right) c_f + m_f\right] b + \\ & \quad - \Psi_b\left(b', b\right) + e \\ & d \geq 0 \\ & \Upsilon' = \tilde{H}\left(s, h_G, \Upsilon; s', h'_G\right), \end{aligned} \tag{C.17}$$

and subject to Equations (2.11) and (2.12).

The algorithm proceeds in three steps. First, I guess the coefficients of the perceived law of motion for Υ and solve for the stochastic discount factor (aggregate kernel). Second, taking the solution from the first step as given, I solve the firm's problem. Third, I simulate the economy and update the perceived law of motion for Υ' accordingly. I iterate on these three steps until convergence on the coefficients of the perceived law of motion.

I approximate all functions using linear interpolation. The firm's idiosyncratic productivity (z) and the aggregate sovereign risk processes (s) are discretized using Tauchen's

[39] 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' balance sheets) could potentially improve the forecastability of Υ'. However, I find that adding first-order moments of firms' capital and debt (or banks' net worth) does not significantly improve the forecast of Υ', but further increases the dimensionality of the problem with the consequent increase in computational time.

method. Grids of evenly distributed points are constructed for all 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.[40]

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

1. Guess 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 $V^r\left(k, b, z, \tilde{\boldsymbol{S}}\right)$ 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.
3. Using the optimal policies computed in step 2, update the pricing function.
4. Iterate until convergence of both $V^r(.)$ and $q(.)$.

Since 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 nonstochastic 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 banks' net worth. In each step of the simulation, I use a simple bisection algorithm to solve for the value of the auxiliary variable Υ that guarantees market clearing in the loan market. I simulate the economy T periods and use the simulated objects to update the coefficients of the perceived law of motion for Υ'. I iterate on this algorithm until convergence of these coefficients.

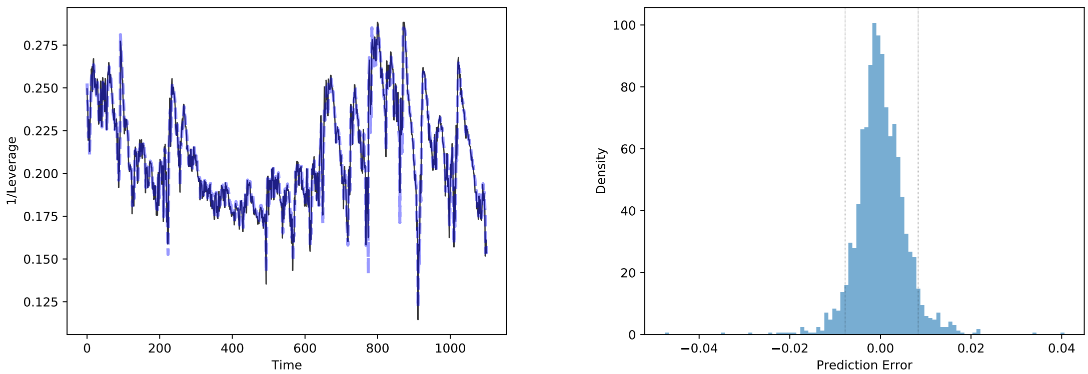
[40] To make a better use of the grid, I re-express the firm's states in terms of capital, leverage (instead of debt), and productivity.

Figure C.4 describes the fit of the predicted law of motion defined in Equation (C.16) when the government is not in default (i.e., $h_G = h'_G = 0$). Panel (a) compares the observed Υ' (black lines) with the one-period prediction $\tilde{H}$ (blue lines) and shows that the forecast closely follows the observed series. Panel (b) shows the histogram for the prediction error $\Upsilon' - \tilde{H}$. The residuals are centered at zero. The 5th and 95th percentiles are -0.0078 and 0.0083 (around 3% of the mean value for Υ). Table C.1 complements the analysis by providing information about the RMSE for the one-period forecast across different aggregate states. The table shows that the predicted law of motion also gives a relatively good fit in those states in which $h_G = 1$ or $h'_G = 1$.

Figure C.4: Predicted Law of Motion - Fit

(a) Prediction vs Observed Value

(b) Prediction Error



Notes: The figure shows the fit of the predicted law of motion for the case in which $h_G = h'_G = 0$. Panel (a) compares the observed Υ' (black lines) with the one-period prediction $\tilde{H}$ (blue dotted lines). Panel (b) reports the histogram for the one-period prediction error. Vertical lines show the 5th and 95th percentile, respectively.

Table C.1: One-period Prediction RMSE

Aggregate State	RMSE
$h_G = 0$; $h'_G = 0$	0.0000301
$h_G = 0$; $h'_G = 1$	0.000167
$h_G = 1$	0.001611

Notes: The table compares the root mean squared error for the one-period prediction across different aggregate states. $RMSE = \frac{1}{T}\sum_{t=1}^{T}\left(\Upsilon'_t - \tilde{H}_t\right)^2$.