The Costs of Sovereign Default: Evidence from the Stock Market

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We use stock market data to test cross-sectional implications of theories of sovereign default and provide a market-based estimate of sovereign default costs. We find that the stock prices of firms vulnerable to financial intermediation disruption, or firms more exposed to the government, are particularly sensitive to changes in sovereign credit spreads. This is consistent with theories in which default is costly because it disrupts financial intermediation and damages government reputation. Estimation of a structural valuation model indicates that the market prices stocks as if sovereign default has large effects on vulnerable stocks, translating to a 12% destruction of the value of their productive assets. (*JEL* G12, G15, G01, F34)

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In the 2012 restructuring of Greek debt, 97% of the bondholders agreed to a 60% haircut on the value of their claims (Zettelmeyer, Trebesch, and Gulati 2013). Creditors accept such large haircuts because there is limited legal recourse, as sovereign debt is weakly enforceable in a court of law. Then why do creditors lend in the first place? It must be because they know sovereigns face costs of some form if they fail to fully repay.

Traditional theories of sovereign debt focus on costs arising from creditor retaliation, such as exclusion from future borrowing and trade sanctions. However, empirical research suggests that creditor retaliation is not a major cost of sovereign default (Panizza, Sturzenegger, and Zettelmeyer 2009; Levy-Yeyati and Panizza 2011; Martinez and Sandleris 2001). Because

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traditional theories lack empirical support, scholars investigate alternative mechanisms through which sovereign default is costly.

The alternative theories propose that sovereign default is costly because it inflicts unintended damage to the defaulting economy. Different theories propose different channels through which damage takes place. This paper tests cross-sectional implications of these theories using European stock market data from 2005 to 2013, a period including the euro sovereign crisis. We find evidence consistent with two cost of default channels: financial intermediation disruption and impaired government relationships.

Recent theories propose that sovereign default is costly because it disrupts domestic financial intermediation (e.g., Gennaioli, Martin, and Rossi 2014a).[1] Disruption occurs because of the following frictions. First, domestic banks hold substantial positions in their sovereign's debt. Second, sovereigns cannot selectively default on foreign bondholders only. Third, domestic firms and consumers rely primarily on domestic banks for finance and cannot easily switch to other sources of capital. Therefore, as sovereign default damages domestic banks' balance sheets, these banks reduce private credit supply, negatively affecting the economy's investment and output.

The financial intermediation disruption channel implies that firms that are particularly vulnerable to disruption should be more strongly affected by the prospect of sovereign default. Our results confirm this prediction. The stock returns of non-financial firms more vulnerable to credit market disruption display much higher sensitivity to contemporaneous changes in sovereign spreads. Specifically, firms in the lowest tercile of corporate asset tangibility and with fragile banking relationships (more syndicated loans lead-arranged by banks from GIIPS countries [i.e., Greece, Ireland, Italy, Portugal, and Spain] or incorporated after 2001) have sovereign risk betas that are three times larger than those of nonvulnerable firms.

Our novel stock market evidence for the financial intermediation disruption channel complements research by Popov and Van Horen (2015) and De Marco (2016). These papers find an association between bank holdings of risky sovereign debt and credit supply contraction during the euro sovereign crisis. Further supporting the disruption channel, Acharya et al. (2016) find that European firms with higher exposure to banks from the eurozone periphery save more and grow less from 2010 to 2012. Their results, however, obtain for non–publicly listed firms only. This would be consistent with equity markets being a "spare tire" that insures listed firms against banking crises (Levine, Lin, and Xie 2016). In turn, we show that prices indicate that access to equity

[1] In addition to Gennaioli, Martin, and Rossi (2014), new theories of sovereign debt focusing on collateral damage through the domestic banking system include Basu (2010), Brutti (2011), Sandleris (2014), Mengus (2014), Sosa-Padilla (2014), Bocola (2016), and Perez (2015). Related theories that also feature the financial intermediation channel of sovereign default include Bolton and Jeanne (2011) and Farhi and Tirole (2014).

markets is not enough to shield listed firms from potential credit disruption stemming from sovereign default.[2]

Cole and Kehoe (1998) propose a different channel: sovereign default is costly because it impairs government relationships through reputation spillovers. Default reveals a government's "type": a government that is shown to be untrustworthy in its relationship with creditors is then viewed as untrustworthy in other relationships. Because governments play a vast role in modern economies, through direct consumption and investment as well as the power to tax and regulate, reputation spillovers from sovereign default can have broad economic consequences. Default can lead to a curtailing of activities in which the private sector contracts with the government directly, or, more broadly, "any type of investment that involves up-front effort or cost for which the government can tax or confiscate proceeds" (Cole and Kehoe 1998, 62).

The reputation spillover channel implies that firms that are relatively more exposed to the government should have higher sovereign risk sensitivity. Consistent with this prediction, we find that firms exposed to the government, either through commercial ties (customer/supplier links or investment partnerships) or through strong regulatory ties, have sovereign risk betas that are twice as large as those of other firms. To our knowledge, we are the first to provide empirical evidence consistent with a government reputation spillover channel for sovereign default costs.

Though the aforementioned results are consistent with cost of default theories, there are alternative interpretations. There are factors that simultaneously affect stock prices and sovereign spreads, such as real productivity shocks, or shocks to the quality of private-sector assets in bank balance sheets, or shocks to the degree of outside imposed fiscal austerity. If these economic factors are not fully spanned by the standard stock market factors we control for, then the sovereign risk sensitivity differences we detect merely proxy for different sensitivities to the omitted factors. To mitigate such concerns, we examine short-window returns following a policy announcement designed to be a shock to probabilities of sovereign default. The cross-section of these announcement returns arguably provides cleaner information about sovereign default than the cross-section of monthly returns across the entire 2005 to 2013 time period.

On July 26, 2012, European Central Bank (ECB) president Mario Draghi delivered the landmark "Whatever-It-Takes" statement. The statement, motivated by the view that the euro sovereign crisis was self-fulfilling, sent a strong signal that the ECB would intervene to reduce sovereign spreads.[3]

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[2] Related research studies the association between sovereign risk and financial firms. Acharya and Steffen (2015) show that eurozone banks with larger holdings of risky sovereign debt are more affected by widening sovereign spreads. Acharya, Drechsler and Schnabl (2014) and Alter and Beyer (2014) examine the feedback loop between sovereign and bank credit risk.

[3] From Draghi's September 6, 2012, press conference: "The assessment of the Government Council is that we are in a situation now where you have large parts of the Euro area in what we call a 'bad equilibrium,' namely an

We find that firms vulnerable to financial intermediation disruption and firms more exposed to the government have higher sovereign risk sensitivity not only in general but also immediately following Draghi's speech.

In addition to testing cross-sectional implications of cost of default theories, we also estimate the cost of sovereign default implicit in market prices. To our knowledge, our paper, and a contemporaneous paper by Jeanneret (2017), have the first estimations of sovereign default costs from stock market data. Both papers rely on structural valuation models. While Jeanneret (2017) identifies the cost of sovereign default through levels of stock volatility and economic data, we do so based on changes in relative valuation levels (price-earnings ratios). Our model allows us to fit (and extrapolate) the association between sovereign spread levels and valuation differences between stocks vulnerable and nonvulnerable to sovereign default.

We find that stocks are priced as if the full effect of sovereign default on vulnerable firms amounts to a decrease in long-term earnings growth and/or an increase in cost of equity capital adding up to 1.27% per year. This translates to a 12% destruction in the value of vulnerable firms' productive assets upon sovereign default. This estimate is probably a lower bound for the overall economy, because our sample only includes large publicly traded firms, which are likely to be less vulnerable to financial intermediation disruption than private firms. We conclude the market prices stocks as if sovereign default imposes economically large costs.

Finally, we investigate two additional channels through which sovereign default could impose costs in the defaulting economy. We do not find cross-sectional evidence of a currency channel through which sovereign default leads to sharp real exchange depreciation and as such impairs corporate balance sheets (Du and Schreger 2015). Similarly, we do not find cross-sectional evidence that sovereign default is costly because it leads to suboptimal reallocation of production away from imported intermediate products toward domestic intermediate inputs, thus reducing an economy's productive efficiency (Mendoza and Yue 2012).

We acknowlege that our results are specific to the eurozone crisis and may not generalize to other sovereign crises. Perhaps the financial disruption channel is particularly important in Europe because of a especially strong "sovereign-bank feedback loop" (Acharya, Drechsler and Schnabl 2014). This strong loop would arise due to relatively high bank holdings of sovereign debt, unusually low-quality bank holdings of private sector debt, and strong government resolve to bail out banks. Perhaps the currency depreciation channel does not obtain in our setting because our sample countries belong to a monetary union, and the threat of expulsion from it may not be credible enough. Future research may examine whether our results obtain in other sovereign debt crises.

equilibrium where you may have self-fulfilling expectations that feed upon themselves and generate very adverse scenarios. So there is a case for intervening to, in a sense, break these expectations."

1. Data

We begin by testing whether nonfinancial stocks more vulnerable to financial intermediation disruption, or nonfinancial stocks more exposed to the government, have greater sensitivity to changes in sovereign spreads. Our independent variables are stock returns. Our dependent variables are changes in sovereign spreads, and such changes interacted with ex ante proxies for credit disruption vulnerability and government exposure. We study eurozone stocks from July 2005 to December 2013, a period that includes the eurozone sovereign crisis. Data are monthly.

1.1 Stock returns

We obtain monthly firm-level, euro-denominated stock market data for eurozone stocks on Datastream. We focus on nonfinancial stocks, as defined by Industry Classification Benchmark (ICB) classifications. In order to highlight the economic relevance of our results, we drop small- and micro-caps from the sample, identified as the smallest stocks whose cumulative market capitalization adds up to 1% of the total eurozone market capitalization at the end of June each year. On average, our sample has 892 stocks each month and a total of 1,375 unique stocks. In addition to stock-level returns, we obtain monthly European four-factor return data from Ken French's website. Ken French's factor returns are U.S. dollar denominated. We use monthly dollar-euro exchange rate data from Datastream to express factor returns in euros.[4]

Table 1 has summary statistics. Panel A shows that we have 90,928 firm-month observations. Firms in our sample are large, with median assets equal to 994 million euros. France, Germany, Italy, and Spain are the countries contributing the most observations to the sample. The average excess stock return across all sample stocks is 0.36% per month, with a standard deviation of 11%. Average stock returns are much higher in Germany (0.73% per month) than in Greece or Italy (–0.72% and –0.01% per month).

1.2 Sovereign spreads

We obtain end-of-month ten-year credit default swaps (CDS) spreads for eurozone countries from Markit. All contracts are euro-denominated and have the Complete Restructuring (CR) clause establishing that any restructuring event triggers payment to the Protection Buyer. Figure 1 plots sovereign CDS spreads over time from 2004 to 2013. Note that spreads diverge strongly starting at the end of 2007.

[4] To avoid double counting, cross-listings are deleted. That is, if an Italian firm is cross-listed in Germany, we use only its Italian stock returns. To avoid using stale Datastream data, we drop observations with three identical consecutive values for return index and market capitalization.

Table 1
Summary statistics

Panel A: Summary statistics by country

Country	N (stock-months)	Excess stock return		Δ Spread		Assets	Vulnerability to financial intermediation disruption: Vulnerability score	Vulnerability to financial intermediation disruption: Low tangibility	Vulnerability to financial intermediation disruption: Fragile banking relationships	Vulnerability to financial intermediation disruption: Young[a]	Vulnerability to financial intermediation disruption: High GIIPS bank dep.[a]	Exposure to the government: Government exposure	Exposure to the government: Commercial relationship	Exposure to the government: Regulatory relationship
		Mean	Std. dev.	Mean	Std. dev.	Median	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Austria	3,271	0.38%	12.64%	0.03%	1.53%	1000	0.143	0.116	0.032	0.034	0.000	0.379	0.235	0.175
Belgium	5,011	0.61%	10.40%	0.05%	1.52%	852	0.450	0.355	0.097	0.066	0.079	0.285	0.150	0.224
Finland	5,752	0.39%	10.75%	0.01%	0.69%	1026	0.453	0.341	0.453	0.137	0.055	0.382	0.351	0.066
France	22,168	0.41%	10.39%	0.04%	1.35%	1134	0.538	0.423	0.116	0.036	0.158	0.395	0.310	0.143
Germany	20,601	0.73%	11.07%	0.02%	0.73%	712	0.395	0.334	0.066	0.050	0.032	0.365	0.252	0.179
Greece	4,493	−0.72%	13.07%	2.15%	13.30%	562	0.233	0.105	0.128	0.000	0.458	0.310	0.261	0.155
Ireland	2,439	0.01%	13.55%	0.11%	3.13%	943	0.546	0.256	0.291	0.128	0.468	0.133	0.048	0.085
Italy	10,978	−0.01%	10.99%	0.15%	2.47%	1033	0.611	0.355	0.392	0.119	0.552	0.364	0.269	0.193
Netherlands	6,347	0.54%	10.47%	0.03%	0.80%	1460	0.490	0.414	0.080	0.039	0.065	0.278	0.232	0.055
Portugal	2,263	0.16%	10.00%	0.38%	4.82%	2096	0.416	0.181	0.275	0.084	0.620	0.305	0.276	0.164
Spain	7,605	0.03%	10.76%	0.14%	2.22%	1395	0.606	0.256	0.383	0.042	0.608	0.437	0.263	0.248
All countries	90,928	0.36%	11.00%	0.17%	3.34%	994	0.474	0.334	0.155	0.054	0.206	0.359	0.263	0.160

a: zeros not imputed for missing data.

(continued)

Table 1
Continued

Panel B: Summary statistics by Vulnerability score *and* Government exposure

	Vulnerability score			Government exposure	
	0	1	2	0	1
Low tangibility	0	0.760	1	0.314	0.369
Fragile banking relationships[a]	0	0.274	1	0.125	0.209
Young[a]	0	0.078	0.531	0.052	0.058
High GIIPS bank dependence[a]	0	0.355	0.746	0.169	0.258
Commercial relationships	0.229	0.292	0.453	0	0.734
Regulatory relationships	0.159	0.159	0.183	0	0.447
Assets	6582	7595	10784	4303	12224
Leverage	0.265	0.230	0.273	0.247	0.259
Cash holdings	0.109	0.162	0.146	0.128	0.139
Profitability	0.117	0.110	0.084	0.123	0.095
N (stock-months)	51,349	36,016	3,563	58,306	32,622

a: zeros not imputed for missing data.

The table has summary statistics of the paper's main variables. The sample consists of large nonfinancial eurozone firms. Data are monthly from July 2005 to December 2013. Stock returns are denominated in euros and from Datastream. Δ *Spread* is normalized change in ten-year euro-denominated sovereign credit default swap (CDS) spreads, as explained in the text. CDS data are from Markit. *Vulnerability score* takes values 0, 1, or 2 and flags firms vulnerable to financial intermediation disruption according to two indicators, *Low tangibility* and *Fragile banking relationships*. *Low tangibility* is a dummy variable flagging firms with asset tangibility in the lowest tercile in a given month. Asset tangibility is defined as property, plant, and equipment scaled by assets using Worldscope data. *Fragile banking relationships* is a dummy variable flagging *Young* firms or firms with *High GIIPS bank dependence*. *Young* is a dummy variable flagging firms incorporated after 2001 using the incorporation year from OSIRIS. *High GIIPS bank dependence* is a dummy variable flagging firms with a high fraction of outstanding syndicated loans lead-arranged by GIIPS banks. Syndicated loan data are from Dealscan. *Government exposure* flags firms that have either *Commercial relationship* or *Regulatory relationship* with the government. *Commercial relationship* identifies firms that are either customers/suppliers or investment partners of eurozone governments. Data are from FactSet Revere. *Regulatory relationship* flags firms in heavily regulated sectors. *Leverage* is defined as total debt scaled by assets. *Cash* is cash and equivalents over assets. *Profitability* is EBITDA over assets. All accounting variables are from Worldscope and winsorized at the 1% level. Panel A has summary statistics grouped by country, while Panel B has statistics grouped by *Vulnerability score* and *Government exposure*.

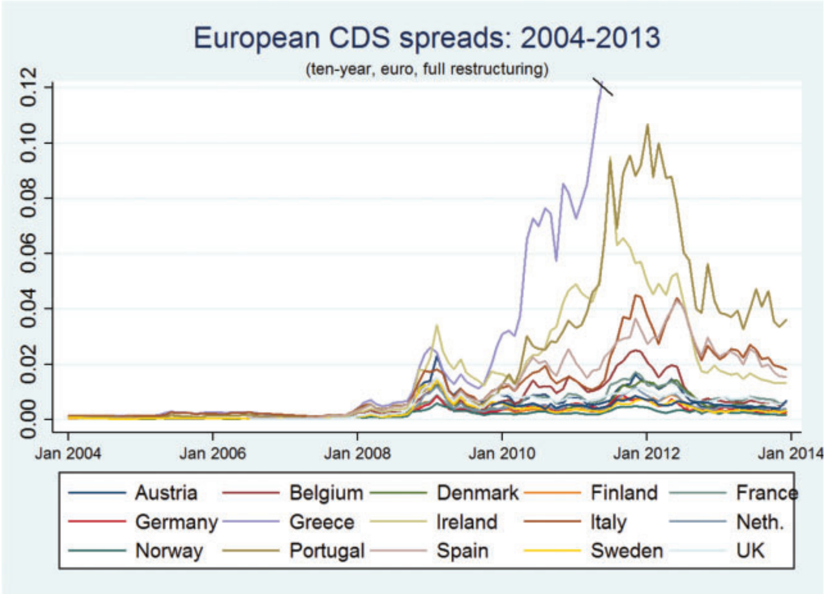

Figure 1
European CDS spreads
The figure shows ten-year eurozone sovereign CDS spreads on a monthly basis from 2004 to 2013. Data are euro-denominated and based on contracts with the Full Restructuring clause. Data are from Markit. Greek sovereign CDS data ends in February 2012 and is capped at 0.13.

To ensure that stock returns and CDS spread changes are in comparable units (i.e., returns), we compute normalized changes in spreads as follows:

$$\Delta Spread_t = \left(Spread_t - Spread_{t-1}\right)\left(\frac{1-\left(1+r_{F,t-1}+Spread_{t-1}\right)^{-10}}{r_{F,t-1}+Spread_{t-1}}\right)$$

where r_F is the ten-year yield on the German Bund minus the ten-year German CDS spread. Thus, our Δ *Spread* variable expresses, approximately, the monthly sovereign spread change as the return on a short position on a ten-year floating-rate sovereign bond.[5] This normalization is useful because, taking a bondholder's perspective, a CDS spread change from 100 to 200 basis points is economically different from a CDS spread change from 2,000 to 2,100 basis points or from one to two basis points.

Panel A of Table 1 shows that the average (normalized) change in sovereign spread Δ *Spread* ranges from 0.01% per month in Finland to 2.15% per month in Greece. The standard deviation of Δ *Spread* across the entire sample is 3.34%, indicating there is considerable time-series and cross-sectional variability.

5 See Equation (3) in Berndt and Obreja (2010). A replication argument implies that the excess return on a floating-rate defaultable bond linked to, for example, a ten-year CDS contract is approximately given by the change in the CDS spread multiplied by the value of a defaultable ten-year annuity.

1.3 Vulnerability to financial intermediation disruption

We assess firms' vulnerability to financial intermediation disruption along two conceptually separate dimensions, corporate asset tangibility and banking relationships. Firms with low asset tangibility have less pledgeable collateral. As such, they are likely to be more negatively affected by a reduction in aggregate credit supply (Holmstrom and Tirole 1997; Almeida and Campello 2007; Manova 2013; Campello and Giambona 2013). Similarly, because relationships are important in mitigating asymmetric information, firms with fragile banking relationships are more vulnerable to negative credit supply shocks.

Banking relationships can be fragile because they are intrinsically weak or because they risk obsolescence. The first case applies to young firms, because they have had less time to develop relationships with lenders (Petersen and Rajan 1994; Chava and Purnanandam 2011). In the euro sovereign crisis, the second case applies to firms with established relationships with banks from distressed sovereigns, because such banks are more exposed to distressed sovereign debt (Acharya and Steffen 2015; Acharya et al. 2016).

The variable *Vulnerability score* assesses a firm's vulnerability to financial intermediation disruption along the corporate asset tangibility and banking relationships dimensions. The score takes values zero, one, and two. It is equal to zero for firms with neither low asset tangibility nor fragile banking relationships. It is equal to one for firms with either low asset tangibility or with fragile banking relationships, but not both. The score is equal to two for firms with both low asset tangibility and fragile banking relationships. The score is additive across the two dimensions of vulnerability because these dimensions are based on separate microeconomic frictions. Below we detail the construction of each of the two *Vulnerability score* components.

Following the literature, we measure asset tangibility each calendar year using property, plant, and equipment (PPE) divided by total assets. Accounting data are from Worldscope. Each month we rank firms based on asset tangibility. We then create the dummy variable *Low tangibility*, flagging firms in the lowest tercile of asset tangibility each month.

We identify firms with fragile banking relations using two proxies, age and dependence on banks from the GIIPS countries. The dummy variable *Fragile banking relationships* is equal to one for firms that are flagged either by the *Young* or by *High GIIPS bank dependence* dummies. The dummy variable *Young* flags firms incorporated after 2001, based on the incorporation date reported in the OSIRIS database. The 2001 year was chosen because the peak of the euro sovereign crisis is 2012, and we assume that firms with ten or more years since incorporation by then have had enough time to develop solid banking relationships. Our definition of *High GIIPS bank dependence* closely follows Acharya et al. (2016), and is detailed below.

We determine GIIPS bank dependence at a given year based on the fraction of the firm's total outstanding syndicated loans that is provided by GIIPS lead arrangers, scaled by the number of lead arrangers in each facility. Data are from Dealscan. We classify a bank as a lead arranger if it is either "mandated lead-arranger," "mandated arranger," or "bookrunner." Acharya et al. (2016) define the "crisis period" for all countries as 2010–2012, and for Greece as 2009–2012. Following Acharya et al. (2016), we keep the GIIPS bank dependence fraction fixed at its pre-crisis level for each crisis year. The dummy variable *High GIIPS bank dependence* takes the value one if a firm's GIIPS bank dependence in a given year is in the top tercile.[6]

Table 1, Panel A, has summary statistics. Across the entire sample, the average *Vulnerability score* is equal to 0.474. The average score ranges from 0.143 for Austrian firms to 0.611 for Italian firms. Austria has the lowest average for the *Fragile banking relationships* dummy, and the second lowest average for the *Low tangibility* dummy. Italy has the highest average for the *Fragile banking relationships* dummy and the third highest average for the *Low tangibility* dummy. By construction, the average *Low tangibility* across all countries is very close to 0.333.

The average *High GIIPS bank dependence* is equal to 0.206. It is not very close to 0.333 because most firms in our sample do not have an outstanding loan provided by a GIIPS lead arranger. Therefore, GIIPS bank dependence is zero for most firms, and all firms with non-zero loan amounts from GIIPS banks are flagged as having *High GIIPS bank dependence.* Because our sample firms tend to be quite old, the average of *Young* is small, equal to 0.054. Because we cannot match all of our Datastream/Worldscope stocks to OSIRIS and Dealscan, and do not impute zeros for missing data for *Fragile relationships* components, the average *Vulnerability score* is not identical to the sum of the average *Low tangibility* and the average *Fragile banking relationships* dummy.

Table 1, Panel B, has summary statistics grouped by *Vulnerability score*. The first four rows show that, as intended, the *Vulnerability score* captures the two dimensions of vulnerability we assess. For the 51,349 observations with *Vulnerability score* equal to 0, both the average *Low tangibility* and the average *Fragile banking relationships* are equal to zero. All 3,563 observations with *Vulnerability score* equal to 2 have *Low tangibility* equal to 1 and either *Young* or *High GIIPS bank dependence* equal to 1, leading to *Fragile banking relationships* equal to 1. The remaining 36,016 observations with *Vulnerability score* equal to 1 have average *Low tangibility* equal to 0.760 and average *Fragile relationships* equal to 0.274.

Table 1, Panel B, shows that, compared with firms with *Vulnerability score* equal to 0, firms with *Vulnerability score* equal to 1 tend to have similar size, leverage, and profitability. However, firms with *Vulnerability score* equal to 1

[6] The variables *Young*, *High GIIPS bank dependence*, and *Fragile relationships* have missing values because we could not find OSIRIS and Dealscan matches for all of our Datastream/Worldscope observations. We match 1,105 (606) of our sample firms to OSIRIS (Dealscan), corresponding to 85% (48%) of our 91,036 firm-month observations. In untabulated regressions we verified that our results are robust to dropping observations with missing data.

tend to have much higher cash holdings as a fraction of assets. This makes sense, as vulnerable firms know their condition and accumulate cash for precautionary reasons. Incidentally, the endogeneity of firms' decisions to hold cash, or take financial leverage, is the reason why these variables are not particularly good measures of vulnerability to financial intermediation disruption. Firms with *Vulnerability score* equal to 2, however, tend to be larger and less profitable than other firms. This difference in size and profitability does not drive our results for *Vulnerability score* because they are robust to dropping the 3,563 observations in which the score is equal to 2.

1.4 Exposure to the government

Through reputation spillovers, sovereign default can be costly because it impairs private-sector relationships with the government (Cole and Kehoe 1998). We assess firms' exposure to this default cost channel along two dimensions, commercial and regulatory relationships. The second dimension lessens concerns about alternative interpretations for our findings. More specifically, there may be channels beyond reputation spillovers through which default impairs government relationships with firms. For example, a default-related tightening of government budget constraints, perhaps driven by outside imposed fiscal austerity, is likely to disproportionately affect firms with commercial ties to the government. However, it is not clear such tightening would disproportionately affect firms exposed to the government via regulatory relationships.

The dummy variable *Commercial relationship* flags firms that have customer/supplier links with, or are investment partners of, governments. Data are from FactSet Revere. The database has firm relationships with different entities, including governments and other firms. We manually identify government entities in the database (e.g., "Government–Italy" and "Ministero del Tesoro"), and then flag firms that Revere identifies as either suppliers/customers or investment partners of governments.[7] The dummy variable *Regulatory relationship* flags firms in heavily regulated European industries: alternative energy, health care, telecommunications, and utilities.

The dummy variable *Government exposure* encompasses both dimensions of government relationships. It is equal to 1 if either *Commercial relationship* or *Regulatory relationship* is equal to 1. Panel A of Table 1 shows that, across the entire sample, the average *Government exposure*, *Commercial relationship*, and *Regulatory relationship* dummy variables are equal to 0.359, 0.263, and 0.160, respectively.

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[7] We match Datastream/Worldscope data to FactSet's Revere by SEDOL and then by name. Out of 1,375 sample firms, 284 are flagged by *Commercial relationship*. Of these 188 are government suppliers, 2 are government customers, 72 are government investment partners, 18 are both customers and investment partners, and 2 are both suppliers and investment partners.

Table 1, Panel B, has summary statistics grouped by *Government exposure*. Because by construction stocks with *Government Exposure* equal to 0 have both *Commercial relationship* and *Regulatory relationship* equal to 0, the average of these dummy variables for nonexposed stocks is equal to 0. The first four columns show that stocks with *Government exposure* equal to 1 tend to have (slightly) higher averages for all four variables that define the *Vulnerability score*. Therefore, we later check whether the effect of exposure to the government on sovereign risk betas is independent of the effect of vulnerability to financial intermediation disruption.

The table also shows that stocks with *Government exposure* equal to 1 tend to be larger and less profitable than stocks with *Government exposure* equal to 0. In untabulated regressions, we show that our results for the *Government exposure* variable are not driven by size or profitability. Specifically, we create size and profitability dummies flagging stocks in the highest size tercile or the lowest profitability tercile. We find that large size or low profitability stocks do not have larger sovereign risk betas than other stocks.

2. Regression Analysis

We test cross-sectional implications of different cost of sovereign default channels. In particular, we verify whether stocks more vulnerable to financial intermediation disruption, or stocks more exposed to governments, display higher sensitivity to changes in sovereign spreads. To that end, we use several different empirical specifications based on either stock-level or country-level regressions using long-short portfolios. Our results are consistent across all specifications. First we focus on the financial intermediation channel, then on the impaired government relationships channel.

2.1 Financial intermediation disruption

The starting point for return regressions is a four-factor model in which individual stock returns are driven by exposure to Europe-wide market, size, value, and momentum factors (*MKT*, *SMB*, *HMB*, and *WML*), plus residual returns. This is consistent with the view that European stock markets are integrated (e.g., Bekaert et al. 2013). We add an additional factor to the standard ones. Individual stocks (indexed by i) are exposed to an additional dimension of systematic risk, namely sovereign risk, which varies at the country level (indexed by C). We capture sovereign risk exposure by sensitivity to sovereign spread changes, Δ *Spread.*

$$r_{i,t} = \alpha + \beta\ \Delta Spread_{C,t} + \gamma_1\ MKT_t + \gamma_2\ SMB_t + \gamma_3\ HML_t + \gamma_4\ WML_t + \varepsilon_{i,t}$$

The financial intermediation theories of sovereign default predict that nonfinancial stocks more vulnerable to financial intermediation disruption have higher sensitivity to sovereign risk, that is, a higher beta with respect to

Δ *Spread.* To test this prediction, we interact Δ *Spread* with the *Vulnerability score* variable. If the coefficient on the interaction term Δ *Spread* $\times$ *Vulnerability score* is negative and statistically significant, then our main hypothesis is confirmed. Because the interaction term captures differences across vulnerability scores for a given Δ *Spread*, which is defined at the country level, our results identify cross-firm differences within a country. To allow for the possibility that vulnerable firms also have higher exposure to the traditional four factors, we also interact each of the four standard factors with *Vulnerability score*.

Table 2 contains results of our stock-level panel regressions for *Vulnerability score*. Because errors are likely to be cross-sectionally correlated at a given point in time, we display *t*-statistics based on standard errors that are time clustered. Column (1) of Table 2, Panel A, has a preliminary result. We examine the contemporaneous correlation between stock returns and sovereign spread changes. Consistent with the literature (Bailey and Chung 1995; Longstaff et al. 2011; Dieckmannm and Plank 2012), we find that stock returns are negatively correlated with sovereign spread changes, after controlling for four factor returns. On average, an increase in sovereign spreads resulting in a 1% change in Δ *Spread* is associated with a 0.127% decrease in stock returns. This sensitivity is statistically significant at the 1% level.

Column (2) of Table 2 (Panel A) shows that stocks vulnerable to financial intermediation disruption have higher sensitivity to sovereign risk. Compared with Column (1), we add interaction terms of our *Vulnerability score* variable with Δ *Spread* and each of the four factors. The interaction coefficient Δ *Spread* $\times$ *Vulnerability score* is equal to –0.086 and statistically significant at the 1% level. The coefficient on Δ *Spread* in the same regression is –0.097. Therefore, the sovereign risk beta of the most vulnerable firms (*Vulnerability score* equal to 2) is nearly three times the sovereign risk beta of the nonvulnerable stocks ($-0.097 - 2 \times 0.086 = -0.269$ versus –0.097). The sovereign risk beta of *Vulnerability score* equal to 1 firms is nearly double that of the nonvulnerable stocks. Consistent with the credit disruption channel, firms that are more vulnerable to financial intermediation disruption are more sensitive to changes in sovereign spreads.

Columns (3) to (8) contain results of robustness checks. In Column (3) the sample period is restricted to the one most closely associated with the European sovereign debt crisis. The period starts in January 2010 instead of July 2005. In Column (4) we restrict the sample to stocks from the GIIPS countries. In Columns (5) and (6) we respectively add interactive industry and country fixed effects. That is, in addition to standard industry or country fixed effects, we have interactions of such fixed effects with Δ *Spread* and each of the four factors. Our conclusions are unchanged. The results in Columns (3) to (6) are qualitatively and quantitatively similar to those in Column (2).

In Column (7) we use a different factor model. We augment the European four-factor model with four local factors. This addresses the possibility of

Table 2
Do firms vulnerable to financial intermediation disruption have higher sovereign risk betas? (Stock level)

Panel A: Vulnerability score

Dependent variable: Excess stock returns	(1)	(2)	2010–2013 (3)	GIIPS only (4)	Industry fixed effects (5)	Country fixed effects (6)	European and local factors (7)	Bank Δ Spread (8)
Δ Spread	−0.127***	−0.097**	−0.086**	−0.087***			−0.138**	−0.052
	(3.27)	(2.55)	(2.37)	(2.51)			(3.95)	(0.85)
Δ Spread × Vulnerability score		−0.086***	−0.078***	−0.079***	−0.068**	−0.065***	−0.114***	−0.089**
		(3.48)	(3.27)	(3.33)	(2.12)	(3.00)	(3.86)	(2.54)
Vulnerability score		−0.004	0.001	0.000	0.000	0.000	−0.001	−0.001
		(0.54)	(1.47)	(0.24)	(0.07)	(0.44)	(0.59)	(0.78)
MKT	1.020***	1.021***	1.065***	1.001***				1.009***
	(29.15)	(26.34)	(16.19)	(19.88)				(23.96)
SMB	0.386***	0.391***	0.381***	0.382***				0.377***
	(8.07)	(7.79)	(4.86)	(5.00)				(5.73)
HML	−0.232***	−0.256***	−0.153*	−0.164**				−0.254***
	(4.49)	(4.68)	(1.69)	(2.07)				(3.81)
WML	−0.224***	−0.216***	−0.245***	−0.303***				−0.201***
	(7.00)	(7.00)	(5.69)	(7.13)				(5.51)
MKT × Vulnerability score		−0.003	−0.038	−0.047				−0.002
		(0.15)	(1.24)	(1.56)				(0.09)
SMB × Vulnerability score		−0.007	−0.092**	−0.100**				−0.004
		(0.20)	(2.04)	(1.99)				(0.09)
HML × Vulnerability score		0.045	0.076	0.092*				0.054
		(1.40)	(1.59)	(1.71)				(1.36)
WML × Vulnerability score		−0.015	−0.014	0.004				−0.029
		(0.67)	(0.61)	(0.09)				(1.15)
Constant	0.002	0.002	0.000	−0.001			0.004	0.002
	(1.37)	(1.45)	(0.12)	(0.28)			(1.48)	(1.62)
Interactive industry fixed effects	No	No	No	No	Yes	No	No	No
Interactive market fixed effects	No	No	No	No	No	Yes	No	No
European and local factors with interactions	No	No	No	No	No	No	Yes	No
N (stock-months)	90,928	90,928	40,206	27,778	90,928	90,928	90,928	80,674
R^2	0.221	0.222	0.176	0.235	0.232	0.227	0.238	0.215

(continued)

Table 2
Continued

Panel B: Components of Vulnerability score

Dependent variable: Excess stock returns	Low tangibility (1)	High GIIPS bank dependence (2)	Young (3)	Fragile banking relationships (4)
Δ Spread	−0.113***	−0.089***	−0.115***	−0.108***
	(3.03)	(2.64)	(3.10)	(2.78)
Δ Spread × Low tangibility	−0.103***			
	(2.65)			
Low tangibility	0.000			
	(0.38)			
Δ Spread × High GIIPS bank dependence		−0.066**		
		(2.16)		
High GIIPS bank dependence		−0.002		
		(1.28)		
Δ Spread × Young			−0.172**	
			(2.21)	
Young			−0.002	
			(1.36)	
Δ Spread × Fragile relationships				−0.057**
				(2.17)
Fragile relationships				−0.002*
				(1.96)
Factors	Yes	Yes	Yes	Yes
Factors × Low tangibility	Yes			
Factors × High GIIPS bank dependence		Yes		
Factors × Young			Yes	
Factors × Fragile relationships				Yes
N (stock-months)	90,928	43,990	77,690	82,376
R^2	0.222	0.247	0.219	0.223

The table shows results of panel regression of stock-level excess returns onto contemporaneous changes on sovereign spreads (Δ *Spread*) and four-factor returns. The sample consists of large nonfinancial eurozone firms. Data are monthly from July 2005 to December 2013. Panel A reports panel regressions of *Vulnerability score* interacted with Δ *Spread*. *Vulnerability score* takes values 0, 1, or 2 and flags firms vulnerable to disruption in financial intermediation as indicated by *Low tangibility* and/or *Fragile banking relationships.* Column (8) has the asset-weighted average change in normalized bank CDS spreads in place of Δ *Spread*. Panel B reports results for each of the components of the *Vulnerability score* separately. Standard errors are clustered at the time level. *T*-statistics are reported in parentheses below the coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

imperfect market integration during our sample period.[8] Local four-factor model data for each of the 11 eurozone countries is from Andrea Frazzini's webpage. Because of the contemporaneous correlation between Δ *Spread* and each local stock market, we follow Acharya and Steffen (2015) and orthogonalize local factors with respect to Δ *Spread.* The interaction term Δ *Spread* $\times$ *Vulnerability score* remains statistically significant at the 1% level using the eight-factor model. Column (7) results are qualitatively similar if local factors are not orthogonalized with respect to Δ *Spread.*

Column (8) contains an additional test that further links our regressions to banks' exposure to sovereign risk. There we use each country's asset-weighted bank Δ *Spread* instead of each country's sovereign Δ *Spread.* This makes sense because our channel operates through firms' exposure to banks' distress, which in turn stems from banks' exposure to sovereign risk. So, instead of measuring stock return sensitivity to changes in a country's sovereign spreads, we can measure sensitivity to the changes in a country's bank spreads.[9]

Column (8) shows that our results are robust. We find that stocks more vulnerable to financial intermediation disruption have higher sensitivity to changes in their country's bank spreads. The coefficient on (bank) Δ *Spread* $\times$ *Vulnerability score* is negative and statistically significant at the 5% level.

In Table 2, Panel B, we report regressions using the individual components of the *Vulnerability score* instead of the score itself. We find that all results are consistent with those of Table 2, Panel A. Specifically, Column (1) shows that firms having *Low tangibility* equal to 1 have sovereign risk betas that are about twice as large as firms with *Low tangibility* equal to zero, and that the difference is statistically significant at the 1% level. Similarly, firms flagged by the *High GIIPS bank dependence*, *Young*, or *Fragile banking relationships* dummy variables have higher sensitivity to sovereign risk.

In sum, consistent with the financial intermediation theories of sovereign default, stock-level panel regressions show that firms that are expected to suffer more from financial intermediation disruption display more sensitivity to sovereign risk. Both dimensions of vulnerability matter: low collateral and fragile banking relationships.

2.1.1 Country-level results. Table 3 contains results of regressions using country-level long-short portfolios. Within each eurozone country, we form

[8] It is possible, however, that market disintegration itself is at least partially caused by the sovereign debt crisis. Bekaert et al. (2011) find that political risk is a determinant of equity market segmentation. Chakraborty et al. (2017) argue that regulatory responses to the crisis increased credit frictions and resulted in cross-border segmentation of financial intermediation.

[9] From Bloomberg, we obtain five-year euro-denominated CDS spreads of individual eurozone banks at the end of each month. For each bank, we compute the monthly normalized change in CDS spread Δ *Spread* using the formula on page 9. Then, for each country with more than just one bank in the sample, we calculate the weighted average of the Δ *Spread* of its banks, with weights determined by total assets at the end of 2007. This bank-based Δ *Spread* measure is noisy for two reasons. First, because there are few banks in the sample (35 banks from 9 countries), bank-specific noise is not fully averaged out. Second, compared with sovereign CDS data, bank CDS data is illiquid.

Table 3
Do firms vulnerable to financial intermediation disruption have higher sovereign risk betas? (Country level)

Dependent variable:	Vulnerability score			Low tangibility			Fragile banking relationships		
Long-short returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Spread	−0.063	−0.062	−0.068	−0.060	−0.074	−0.084	−0.060	−0.044	−0.046
White	(3.04)***	(2.84)***	(3.13)***	(3.17)***	(3.90)***	(4.21)***	(2.10)**	(1.71)*	(1.59)
Driscoll Kraay	(4.19)***	(3.73)***	(3.60)***	(2.79)***	(4.50)***	(4.48)***	(2.77)***	(1.95)*	(1.95)*
Time-clustered	(2.91)***	(2.64)***	(2.95)***	(2.94)***	(3.67)***	(3.96)***	(2.17)**	(1.64)*	(1.57)
Factors	No	Yes	Yes	No	No	Yes	No	No	Yes
Factors × Country dummies	No	No	Yes	No	No	Yes	No	No	Yes
N (country-months)	1,094	1,094	1,094	1,094	1,094	1,094	1,055	1,055	1,055

The table shows regressions of stacked country-level long-short portfolio returns on contemporaneous changes in sovereign spreads (Δ *Spread*). Long-short portfolios within each eurozone country are based on *Vulnerability score*, *Low tangibility,* or *Fragile banking relationships*. Portfolios are equally weighted, and consist of large nonfinancial eurozone firms. Data are monthly from July 2005 to December 2013. For each of the portfolio forming variables, we report results of three regressions: excluding four-factor returns, including four-factors returns, and including interactions of four-factor returns and country dummies. Below the coefficients, we report t-statistics based on three types of standard errors: White, Driscoll-Kraay (four lags), and time-clustered. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

equal-weighted portfolios that are long stocks with *Vulnerability score* greater than zero and short the remaining stocks with *Vulnerability score* equal to zero. Long-short portfolio returns are regressed onto contemporaneous changes in sovereign spreads and four-factor returns. The 11 eurozone long-short portfolios are stacked to explore not only time series but also cross-country variation in Δ *Spread*. We report three types of standard errors: White, Driscoll-Kraay, and clustered at the time level.

Columns (1) to (3) report results of regressing equal-weighted *Vulnerability score* long-short portfolio returns on changes in sovereign spreads. Columns (2) and (3) control for the four factors, that is, they allow for the possibility that long and short portfolios based on *Vulnerability score* have different exposures to *MKT*, *HML*, *SMB*, and *WML*. In Column (3) we add interactions of each of the four factors with country dummies, to allow for different four factor betas for each of the 11 long-short country portfolios.

The results in Columns (1) to (3) indicate that portfolios of vulnerable stocks have higher exposure to sovereign risk than portfolios of nonvulnerable stocks. The coefficient on Δ *Spread* is negative in all these columns. The coefficients are statistically significant at the 1% level using all types of standard errors.

Columns (4) to (9) have results using the components of the *Vulnerability score*. Results show that both *Low tangibility* and *Fragile banking relationships* contribute to vulnerable stocks' higher sovereign risk sensitivity. We form equal-weighted long-short portfolios based on *Low tangibility* or on *Fragile relationships*. The coefficient on Δ *Spread* is negative in Columns (4) to (9). For *Low tangibility*, the coefficient is statistically significant at the 1% level in all specifications. For *Fragile relationships* the coefficient is significant in some specifications, and borderline insignificant in others. Nonetheless, the economic magnitudes of the Δ *Spread* coefficients are similar to for portfolios based on *Vulnerability score* and *Low tangibility*.

In sum, country-level results agree with stock-level results. Stocks more vulnerable to financial intermediation disruption have larger sovereign risk betas. This result is driven by both dimensions of vulnerability, low collateral and fragile banking relationships. This supports the financial intermediation theories of sovereign default by Gennaioli, Martin, and Rossi (2014) and others.

2.2 Exposure to the government

Table 4, Panel A, tests whether firms more exposed to governments, and thus with a higher risk of impaired government relationships, have higher sensitivity to sovereign risk. As in Table 2, we regress individual stock returns onto normalized changes in CDS spreads (Δ *Spread*), including an interaction term with government relationship dummies. We control for exposure to the standard four stock return factors.

Column (1) shows that the coefficient on the interaction term Δ *Spread* $\times$ *Government exposure* is negative and statistically significant at the 1% level. The effect is economically large: stocks with *Government exposure* equal to 1

Table 4
Do firms more exposed to the government have higher sovereign risk betas?

Panel A: Stock level

Dependent variable: Excess stock returns	(1)	(2)	(3)	2010–2013 (4)	GIIPS only (5)	European and local factors (6)	(7)
Δ Spread	−0.096***	−0.106***	−0.112**	−0.082***	−0.079***	−0.141**	−0.074**
	(3.05)	(3.05)	(3.10)	(2.67)	(3.01)	(3.91)	(2.35)
Δ Spread × Government exposure	−0.083***			−0.082***	−0.092***	−0.095***	−0.071**
	(2.72)			(3.01)	(2.79)	(3.79)	(2.29)
Δ Spread × Commercial relationship		−0.063**					
		(2.34)					
Δ Spread × Regulatory relationship			−0.097***				
			(3.08)				
Δ Spread × Vulnerability score							−0.074***
							(2.96)
Government exposure	0.000			−0.002	0.001	0.001	0.000
	(0.20)			(1.61)	(0.57)	(0.66)	(0.26)
Commercial relationship		0.000					
		(0.34)					
Regulatory relationship			−0.002				
			(1.17)				
Vulnerability score							−0.001
							(0.60)
Factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factors × Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (stock-months)	90,928	90,928	90,928	40,206	27,778	90,928	90,928
R^2	0.222	0.222	0.235	0.236	0.236	0.238	0.222

(continued)

Table 4
Continued

Panel B: Country level

Dependent variable:	Government exposure			Commercial relationship			Regulatory relationship		
Long-short returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Spread	−0.050	−0.076	−0.087	−0.083	−0.076	−0.078	0.007	−0.077	−0.084
White	(1.87)*	(2.60)***	(2.75)***	(2.86)***	(2.66)***	(2.41)**	(0.23)	(2.99)***	(3.15)***
Driscoll Kraay	(2.29)**	(3.78)***	(2.94)***	(3.74)***	(4.13)***	(3.64)***	(0.19)	(3.82)***	(2.87)***
Time-clustered	(1.78)*	(2.56)**	(2.64)***	(2.89)***	(2.65)***	(2.41)**	(0.21)	(2.98)***	(2.88)***
Factors	No	Yes	Yes	No	No	Yes	No	No	Yes
Factors × Country dummies	No	No	Yes	No	No	Yes	No	No	Yes
N (country-months)	1,094	1,094	1,094	1,082	1,082	1,082	1,094	1,094	1,094

The table shows results of regressions of excess stock returns onto contemporaneous changes on sovereign spreads (Δ *Spread*). The sample consists of large nonfinancial eurozone firms. Data are monthly from July 2005 to December 2013. Panel A has stock-level regressions. *Government exposure* flags firms that have either *Commercial relationship* or *Regulatory relationship* with the government. All regressions include four-factor returns and interactions of four-factor returns with either *Government exposure*, *Commercial relationship*, or *Regulatory relationship*. Standard errors are clustered at the time level. T-statistics are reported in parentheses below the coefficients. Panel B shows regressions of equally weighted stacked country-level long-short portfolio returns formed on *Government exposure*, *Commercial relationship* or *Regulatory relationships.* We report White, Driscoll-Kraay (four lags), and time-clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

have sovereign risk betas that are about twice as large as other firms (–0.179 = –0.096–0.083 versus–0.096).

Columns (2) and (3) show that both commercial and regulatory relationships drive the result in Column (1): the coefficients on both Δ *Spread* $\times$ *Commercial relationship* and Δ *Spread* $\times$ *Regulatory relationship* are statistically significant at the 5% level in separate regressions.

Columns (4) and (5) show that Column (1) result also obtains in the 2010–2013 period, and in the subsample of GIIPS stocks. Column (6) shows that the result is robust to using an eight-factor model that augments the European four-factor model with a local four-factor model. Column (7) shows that both Δ *Spread* $\times$ *Government exposure* and Δ *Spread* $\times$ *Vulnerability score* are negative and statistically significant when included as regressors.

Table 4, Panel B, shows that long-short portfolio regressions confirm the results of stock-level regressions. As in Table 3, within each country we form equal-weighted portfolios long stocks with *Government exposure* equal to 1, and short stocks with *Government exposure* equal to 0. Such long-short portfolio returns are regressed on Δ *Spread.* We report results with and without controlling four-factor returns, and when controlling for four-factor returns, with or without interactions of four-factors with country dummies.

The table shows that stocks with higher government exposure have higher sensitivity to sovereign risk. When controlling for four factor returns in Columns (2) and (3), our preferred specifications, the coefficients on Δ *Spread* are negative and statistically significant at the 5% level according to all types of standard errors. When we do not control for four-factor returns, the coefficient on Δ *Spread* drops in magnitude but remains statistically significant at the 10% level.

In Columns (4) to (9) we separately examine the components of *Government exposure*. When controlling for four factor returns, both commercial and regulatory relationships with the government contribute to a firm's higher sensitivity to sovereign risk. The coefficients on Δ *Spread* in Columns (5), (6), (8), and (9) are negative and statistically significant at the 5% level for all standard error types. When not controlling for four factor returns, the coefficient on Δ *Spread* is negative and statistically significant in the *Commercial relationship* regression, but positive, economically small, and statistically insignificant in the *Regulatory relationship* regression.

Untabulated coefficients show that controlling for four-factor returns is important because stocks with *Regulatory relationship* equal to 1 have lower market betas than stocks with *Regulatory relationship* equal to 0. Because of the negative contemporaneous correlation between Δ *Spread* and market returns, and market beta differences, regressions that do not control for the market factor do not correctly assess the long-short portfolio's true sensitivity to sovereign risk. In sum, different testing approaches show that stocks more exposed to the government have higher sensitivity to sovereign risk. This higher sensitivity is driven both by commercial relationships (customer/supplier or investment links) and by regulatory relationships. Our findings indicate that the market prices stocks as if sovereign default negatively affects the economy through impaired government relationships. This result is consistent with Cole and Kehoe (1998) reputation spillovers theory.

2.3 Additional robustness checks

In this section we report robustness checks. First we use an alternative proxy for vulnerability to financial intermediation disruption. Then we revisit stock- and country-level results using alternative empirical specifications. The results confirm that stocks vulnerable to financial intermediation disruption, and stocks more exposed to the government, are more sensitive to sovereign risk.

2.3.1 External finance dependence. Appendix Table A1 has results using the Rajan-Zingales external finance dependence measure (Rajan and Zingales 1998). Firms in economic sectors with intrinsically larger dependence on external finance to fund capital expenditures are also likely to be more strongly affected by aggregate credit disruption. The dummy variable *High EF dependence* flags firms in the highest tercile of the Rajan-Zingales metric.[10] The coefficient on the Δ *Spread* $\times$ *High EF dependence* interaction term is –0.070 and statistically significant at the 1% level, while the coefficient on Δ *Spread* is –0.108. Thus, *High EF dependence* firms have sovereign risk betas (–0.108 – 0.070) that are 65% larger than those of other firms.

2.3.2 Stock-level results. Appendix Table A2 has several robustness checks for stock-level results. First, we obtain the sovereign risk beta of each individual stock by running one time-series regression of monthly excess returns onto Δ *Spread* and the four European stock factors. Results are tabulated in Panel A. There are 731 mostly nonvulnerable firms with (mode) *Vulnerability score* equal to 0, and 602 mostly vulnerable firms with (mode) *Vulnerability score* equal to 1 or 2. There are 905 stocks with *Government exposure* equal to 0, and 428 stocks with *Government exposure* equal to 1. The median sovereign risk beta of mostly vulnerable firms is –0.137, which is larger in magnitude than the median sovereign risk beta of mostly nonvulnerable firms (–0.004). Similarly, the median sovereign beta of firms with *Government exposure* equal to 1 is –0.199, larger than the median beta of stocks with *Government exposure* equal to 0 (0.017). The differences of the medians are statistically significant at the 5% level in both cases.

Second, Panel A of Appendix Table A2 reports results of a seemingly unrelated regressions (SUR) approach. We collect the coefficients of a SUR

[10] We use the Rajan-Zingales metric by ISIC sector from Claessens and Laeven (2003), generously provided to us by Luc Laeven, and the firm's ISIC classification from OSIRIS. We assign firms without an ISIC code the average Rajan-Zingales metric for firms in the same Level 3 sector according to the Industry Classification Benchmark on Datastream.

system with two panel regressions of monthly stock returns onto Δ *Spread* and the four factors: one regression for firms with *Vulnerability score* equal to 0, and the other for firms with *Vulnerability score* greater than 0. The sovereign risk beta coefficient of vulnerable stocks is –0.161, greater in magnitude than the –0.102 coefficient for nonvulnerable stocks. The difference is statistically significant at the 5% level. Analogously, the SUR system for stocks grouped by *Government exposure* produces consistent results. The sovereign risk beta coefficient of stocks with government exposure is –0.180, greater in magnitude than the –0.096 coefficient for nonexposed stocks. The difference is statistically significant at the 1% level.

Third, we use time-varying stock-level betas. Specifically, we estimate individual stock betas with respect to Δ *Spread* using rolling one-year regressions with weekly data. In addition to Δ *Spread*, beta estimation regressions include either European four factors or an eight-factor model that combines local and European stock factors. As before, local factors are orthogonalized with respect to Δ *Spread* as in Acharya and Steffen (2015). The eight-factor model accomodates the possibility of time-varying market integration during our sample period.

Panel B of Appendix Table A2 shows results of median regressions of weekly sovereign risk betas on *Vulnerability score* or *Government exposure*. Regressions include additive time fixed effects, and standard errors are clustered at the stock level. Columns (1) and (4) show that our baseline results obtain in these alternative specifications. Stocks with high *Vulnerability score* or high *Government exposure* have higher sensitivity to changes in sovereign spreads, after controlling for exposure to known stock factors. Columns (2) and (5) restrict the sample to GIIPS stocks, while Columns (3) and (6) restrict the sample to 2010–2013. The results are robust in both cases.

In an untabulated regression, we partially address one difficulty arising from the twin nature of sovereign and banking crises. Sovereign spreads may reflect concerns about government bailouts of national banking systems. In that case, our results would be consistent with sovereign CDS spreads merely proxying for the health of the banking sector, even before accounting for any effect of sovereign default on the health of the banking sector. To mitigate this concern, we repeat our baseline specifications excluding firms from Spain and Ireland, two countries in which the aforementioned concerns seem sharper. We find that results in Table 2 (Column 2) and Table 4 (Columns 1 and 7) still obtain in the reduced sample. That is, stocks with high *Vulnerability score* or high *Government exposure* have higher sensitivity to changes in sovereign spreads.

2.3.3 Country-level results. Appendix Table A3 has alternative specifications for country-level results. We repeat the tests using value-weighted instead of equal-weighted long-short portfolios. We also repeat the tests using an eight-factor model that combines European and local four factors (with local factor orthogonalized with respect to Δ *Spread*). Consistent with the results in Table 3, we find that the coefficient on Δ *Spread* is negative and statistically significant in all specifications.

In sum, a battery of checks indicates that our baseline results in Tables 2 to 4 are broadly robust: stocks vulnerable to financial intermediation disruption, and stocks more exposed to the government, display higher sensitivity to sovereign risk.

2.4 Announcement returns

Our stock- and country-level regressions show that stocks more vulnerable to financial intermediation disruption, or stocks more exposed to the government, display higher sensitivity to changes in sovereign spreads. We control for exposure to known stock market factors. The results are consistent with sovereign default being costly because it disrupts domestic financial intermediation and impairs government relationships.

However, it is possible that vulnerable stocks are more sensitive to sovereign spread changes because they are also more exposed to omitted factors correlated with spreads and unspanned by the standard stock market factors we control for. Candidate omitted factors include real productivity shocks, shocks to the quality of private-sector assets in bank balance sheets, and shocks to the degree of outside imposed fiscal austerity. In this section we get one step closer to identifying sovereign risk effects by conducting an event study.

On July 26, 2012, Mario Draghi, the president of the European Central Bank (ECB), spoke at the Global Investment Conference in London. Amid concerns that countries would default on their debts and destabilize the monetary union, Draghi stated "Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough." This statement, motivated by the ECB's view that the European sovereign crisis was a self-fulfilling one, was designed to be an exogenous shock to probabilities of sovereign default. Therefore, we can more cleanly extract information about sovereign default from the cross-section of announcement returns than from the cross-section of monthly returns over the entire 2006 to 2013 period.

Draghi's announcement elicited strong, positive reaction in sovereign spread and stock markets. The average Δ *Spread* (sovereign spread change in unit of returns) and stock return in the three-day period following the speech are -2.40% and 3.67% respectively. Not surprisingly, the reaction was much stronger in some countries than others. For example, the average Δ *Spread* and stock return are, respectively, –4.98% and 6.45% for Italy, while they are just 0.10% and –0.06% for Germany.[11]

Table 5 shows that vulnerable firms display higher sensitivity to sovereign risk following the announcement. We regress stock returns following Draghi's

[11] The stock returns in this paragraph refer to the large nonfinancial firms in our sample. Using a sample of the largest 270 financial firms in the eurozone, we calculate that the average announcement return was 4.7% (8.4% for GIIPS, and 3.2% for the other countries).

Table 5
Do vulnerable firms have higher sensitivity to sovereign spreads following a policy announcement?

						Weekly factor loadings	
Dependent variable: Announcement stock returns	(1)	(2)	(3)	(4)	(5)	Stock returns (6)	Abnormal returns (7)
Δ Spread	−0.61***	−0.423***	−0.490**	−0.492***	−0.384**	−0.351**	−0.450**
	(4.38)	(2.93)	(2.41)	(2.74)	(2.27)	(2.44)	(3.12)
Δ Spread × Vulnerability score		−0.173***			−0.141***	−0.145***	−0.166***
		(6.59)			(2.80)	(4.03)	(4.10)
Δ Spread × Government exposure			−0.247	−0.294	−0.188	−0.112	−0.044
			(1.02)	(1.58)	(0.79)	(0.59)	(0.24)
Vulnerability score		0.004*			0.004**	0.001	−0.002
		(1.91)			(1.99)	(0.57)	(1.09)
Government exposure			0.007	0.005	0.007	0.006	0.004
			(1.50)	(1.24)	(1.46)	(1.14)	(0.60)
Factor loadings	No	Yes	Yes	Yes	Yes	Yes	No
Industry fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes
N (stocks)	795	795	795	795	795	790	790
R^2	0.125	0.233	0.234	0.211	0.240	0.295	0.117

The table has regressions of three-day returns following Mario Draghi's "Whatever-it-takes" speech onto contemporaneous changes in sovereign CDS spreads (Δ *Spread*). Four-factor loadings in Columns (2) to (5) are estimated using monthly data from June 2005 to December 2013 and the Fama-French European factors. Factor loadings in Column (6) are estimated using weekly data one year prior to the event and weekly European factor returns from Frazzini. Column (7) uses abnormal returns as the dependent variable, where abnormal returns are defined using the factor loadings in Column (6) and three-day European factor returns from Frazzini. Industry fixed effects based on Level 3 ICB classification. Country-clustered standard errors are displayed below coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

speech onto contemporaneous changes in sovereign spreads (Δ *Spread*) and such changes interacted with *Vulnerability score* and *Government exposure*. This approach allows pooling data from all euro countries in one single regression, even though each country market reacted differently to the announcement. The interaction terms Δ *Spread* × *Vulnerability score* and Δ *Spread* × *Government exposure* measure, for a given spread change, how much more vulnerable firms reacted to the announcement compared to nonvulnerable firms. We control for industry membership and for betas with respect to the four European stock market factors, calculated at the individual stock level using monthly data from June 2005 to December 2013.

Column (1) has a preliminary result. It shows that, not surprisingly, stock returns increased more strongly following the announcement in countries in which sovereign spreads decreased more strongly. Column (2) shows that the coefficient on Δ *Spread* × *Vulnerability score* is statistically significant at the 1% level. That is, for a given Δ *Spread*, stocks vulnerable to financial intermediation disruption reacted more strongly than nonvulnerable stocks. For example, because the Δ *Spread* for Italy was –4.98%, Column (2) estimates imply that Italian stocks with *Vulnerability score* equal to 1 on average had announcement returns that were 1.26% (0.173 ×0.0498 + 0.0040) higher than Italian stocks with *Vulnerability score* equal to 0, after controlling for betas and industry differences.

Because the coefficient on the interaction term Δ *Spread* × *Government exposure* is negative, Column (3) shows that stocks vulnerable to impaired government relationships on average reacted more strongly to a given change in Δ *Spread*. However, the effect is not statistically significant, despite being more economically significant than that of *Vulnerability score*. To investigate further, in Column (4) we remove industry fixed effects. The coefficient on the *Government exposure* interaction term increases in magnitude and approaches statistical significance at the 10% level (t-stat = 1.58). We conclude that, because the definition of *Government exposure* relies (partially) on industry membership, part of the effect of *Government exposure* is subsumed by the industry fixed effects.

In Column (5) we add both interaction terms simultaneously and find that conclusions remain unchanged. The coefficient on Δ *Spread* × *Vulnerability score* remains statistically significant at the 1% level. The coefficient on Δ *Spread* × *Government exposure* remains larger in magnitude than that of Δ *Spread* × *Vulnerability score,* but still is statistically insignificant.

In Columns (6) and (7) we use four-factor loadings estimated using one year of weekly return data ending just before the event. Data are from Andrea Frazzini's webpage. In Column (6) we repeat the specification in Column (5) using weekly one-year betas rather than monthly full-sample betas. The conclusions are unchanged.

The regression in Column (7) has a different way to control for exposure to known stock market factors. Instead of using raw stock returns in the left-hand side and four-factor loadings on the right-hand side as in Columns (2) to (6), we use abnormal returns on the left-hand side and drop factor loadings from the right-hand side. As usual, abnormal returns are defined using the four-factor loadings and factor realizations following the announcement. The conclusions are unchanged: the coefficient on Δ *Spread* × *Vulnerability score* remains statistically significant at the 1% level, while the coefficient on Δ *Spread* × *Government exposure* is negative but not statistically significant.

In untabulated regressions we explore two additional specifications for Columns (6) and (7). We remove industry fixed effects from Columns (6) and (7) and find that the coefficient on Δ *Spread* × *Government exposure* becomes much larger in magnitude in both cases. In Table 5, industry fixed effects partially absorb the effect of *Government exposure*. We also use eight- instead of four-factor loadings, estimated using European and local factors (the latter orthogonalized with respect to contemporaneous Δ *Spread*). We find that the conclusions are unchanged then as well.

Overall, our event study confirms that vulnerable stocks have larger sensitivity to sovereign risk not just in general, but also immediately following a critical policy announcement that was meant to reduce probabilities of sovereign default. However, event study results are more robust for vulnerability to financial intermediation disruption than for exposure to the government.

3. Estimating Sovereign Default Costs

The previous section shows that vulnerable firms' stock returns have higher sovereign risk sensitivity. In this section we use a simple valuation model to assess the economic significance of such sensitivity. The model allows us to back out the full effect of sovereign default that is implicit in market prices. To that end, the model fits (and extrapolates) the empirical association between sovereign spreads and the P/E ratio differential across vulnerable and nonvulnerable stocks in the same country and industry. Model estimation shows that the market expects sovereign default to have an economically large effect on vulnerable firms.[12]

The model, adapted from Andrade (2009), assumes that sovereign default reduces long-term earnings growth and increases the cost of equity capital for vulnerable stocks. Such assumption is consistent with our earlier results showing that vulnerable firms' stock returns are more sensitive to sovereign risk. In fact, in Appendix A we show that the higher sovereign risk sensitivity of vulnerable firms' returns is fully attributable to the higher sensitivity of P/E ratios. This is because the forecasted earnings of vulnerable firms over the short term (nearest three years) are not more sensitive to sovereign risk than those of nonvulnerable firms. Therefore, the higher sovereign risk sensitivity of vulnerable stocks reflects market concerns about long-term earnings growth (and/or cost of capital), as opposed to concerns about near-term earnings.

The model is as follows. Let a country have foreign debt requiring a continuous and constant payment flow $c > 0$. The total foreign debt service is composed of coupon and principal payments. The country continuously retires a fraction $\frac{1}{L}$ of its total debt, replacing it by newly issued debt with the same principal value and coupon rate. Leland (1994, 1998) shows that this framework allows for constant total debt service and finite average debt maturity L, while total payments are exponentially declining for each debt vintage.

The country can default on its foreign debt. After default, the debt payment flow is reduced to $0 < \overline{c} < c$. That is, the recovery rate on defaulted sovereign debt is $R = \frac{\overline{c}}{c}$. After default, total payments are also composed of coupon and principal payments retired at a rate $\frac{1}{L}$, so that average debt maturity after default remains L. Let the average yield spread on outstanding sovereign debt be S_t and the risk-free rate be r. The following proposition shows how the risk-neutral probability of default implied by sovereign debt values, denoted Q_t, relates to S_t, R, r, and L.

12 In the previous section, vulnerability could be due to either financial intermediation disruption or government exposure. Recall that government exposure is identified partly based on industry membership. Because the structural model on this section relies on P/E ratio differentials within the same country and industry, this section focuses on vulnerability to financial intermediation disruption.

Proposition 1. The risk-neutral sovereign default probability is equal to

$$Q_t = \frac{S_t}{(1-R)\left(S_t + r + \frac{1}{L}\right)} \tag{1}$$

Proof. See Appendix B. ■

Vulnerable stocks will be directly affected by sovereign default, while nonvulnerable stocks will not. The model focuses on such difference across stocks within a country. Let the earnings flow of a nonvulnerable stock follow a geometric brownian motion (GBM) with trend μ_x, volatility of earnings growth σ_x, and correlation ρ_x with the global pricing kernel. Assume the global pricing kernel follows a GBM with trend equal to (minus) the international risk-free rate r and volatility equal to (minus) the global price of risk λ. Therefore, the cost of equity capital (or discount rate) of the nonvulnerable stock is equal to $d = r + \lambda \rho_x \sigma_x$ and its earnings yield (inverse P/E ratio) is $(\frac{E}{P})^{non-vuln.} = d - \mu_x$.

Now consider a vulnerable stock that is otherwise comparable to the nonvulnerable stock above. That is, though vulnerable and nonvulnerable stocks are driven by separate GBM processes, such processes have identical parameters. Unlike the nonvulnerable stock, vulnerable stock is directly affected by sovereign default. After default, the vulnerable stock experiences a higher cost of equity capital ($\overline{d} > d$) and a lower earnings growth rate ($\overline{\mu_x} < \mu_x$). Define the cost of default K_0 as the sum of the increase in the cost of equity capital and the decrease in earnings growth rate following sovereign default:

$$K_0 \equiv \left(\overline{d} - d\right) + (\mu_x - \overline{\mu_x}) \tag{2}$$

The vulnerable stock trades at a discount relative to the nonvulnerable one. This discount arises because stock prices reflect the possibility of a negative regime change following sovereign default. If such regime change tends to happen in bad economic times, there will also be a systematic risk premium associated with the discount, above and beyond the likelihood of the regime change alone.

Define the value discount (*VD*) as the relative P/E differential between the vulnerable and the nonvulnerable stock:

$$VD_t \equiv \frac{\left(\frac{P}{E}\right)^{non-vuln.} - \left(\frac{P}{E}\right)_t^{vulnerable}}{\left(\frac{P}{E}\right)^{non-vuln.}} \tag{3}$$

The following proposition shows how to link the value discount to the risk-neutral probability of sovereign default.

Proposition 2. Let the country default the first time a geometric brownian motion Y_t with trend μ_y and volatility σ_y hits an exogenous lower barrier $\overline{Y}$.[13]

[13] Because the stochastic process Y_t can be correlated with the pricing kernel, the risk-neutral probability of default Q_t can diverge from its physical counterpart, as in Borri and Verdelhan (2012).

Let the correlations of Y_t with the earnings flow of the stock and with the global pricing kernel be ρ_{xy} and ρ_y, respectively. Then the value discount is equal to

$$VD_t = \frac{K_0}{(\frac{E}{P})^{non-vuln.} + K_0} Q_t^{K_1} \tag{4}$$

where

$$K_1 = \frac{\frac{1}{2} - \frac{\mu_y - \lambda\sigma_y\rho_y}{\sigma_y^2} - \frac{\rho_{xy}\sigma_x}{\sigma_y} - \sqrt{\left(\frac{1}{2} - \frac{\mu_y - \lambda\sigma_y\rho_y}{\sigma_y^2} - \frac{\rho_{xy}\sigma_x}{\sigma_y}\right)^2 + \frac{2}{\sigma_y^2}(r + \lambda\sigma_x\rho_x - \mu_x)}}{\frac{1}{2} - \frac{\mu_y - \lambda\sigma_y\rho_y}{\sigma_y^2} - \sqrt{\left(\frac{1}{2} - \frac{\mu_y - \lambda\sigma_y\rho_y}{\sigma_y^2}\right)^2 + \frac{2}{\sigma_y^2} r}} > 0$$

Proof. See Appendix B. ■

Equation (4) shows that two parameters, K_0 and K_1, govern the link between the value discount and the risk-neutral probability of sovereign default. The parameter K_0 determines the cost of sovereign default, as defined in Equation (2). The parameter K_1 governs the translation from a bond-based to a stock-based risk-neutral default probability. In general, K_1 is different from one, so the relationship between value discount and risk-neutral default probabilities is nonlinear.

Moreover, note that Equation (4) shows that the value discount is equal to $K_0 \div ((\frac{E}{P})^{non-vuln.} + K_0)$ when the probability of default is equal to one. So, the model allows us to estimate the full value destruction associated with sovereign default by fitting and extrapolating the nonlinear association between sovereign spreads and value discounts before default.

The parameters K_0 and K_1 can be obtained by maximum likelihood estimation of Equation (4). To that end, we allow for additive specification/measurement errors ε_t. We assume that such errors are independent and identically distributed with a normal distribution, but do not impose that they are mean zero (because they are measurement and specification as opposed to forecast errors). To take the model to the data, we allow for time variation in the parameters $(\frac{E}{P})^{non-vuln.}$, R, L, and r. We acknowledge this introduces tension between the model and the estimation, but solving the model with time-varying parameters is beyond the scope of this paper. Thus, our estimation equation is:

$$VD_t = \frac{K_0}{\left(\frac{E}{P}\right)_t^{non-vuln.} + K_0} Q_t^{K_1} + \varepsilon_t, \text{ with } Q_t = \frac{S_t}{(1-R_t)\left(S_t + r_t + \frac{1}{L_t}\right)}. \tag{5}$$

3.1 Model estimation

We need to define sets of comparable stocks in order to compute Equation 4's VD_t and $\left(\frac{E}{P}\right)_t^{non-vuln.}$. We postulate that stocks in the same country and industry are comparable. The industry grouping follows

Bekaert et al. (2007, 2011, 2013), who propose that, under economic and financial integration, stocks in the same industry should have the same growth opportunities and discount rates. Within each country-industry set of comparable stocks, vulnerable stocks have *Vulnerability score* greater than 0, and nonvulnerable stocks have *Vulnerability score* equal to 0.

We compute quarterly VD_t and $\left(\frac{E}{P}\right)_t^{non-vuln.}$ for industry-country pairs of vulnerable and nonvulnerable stocks as follows. First, we obtain quarterly earnings-price (E/P) ratios for individual stocks in our sample using near-term (up to three years) mean earnings forecasts from I/B/E/S. Quarterly data are used in order to mitigate concerns that earnings forecasts are stale: I/B/E/S drops forecasts older than 105 days. These mean forecasts are as of the third Thursday of the month for March, June, September, and December. We average EPS forecasts for the current fiscal year, the next fiscal year, and the fiscal year after that. These average three-year EPS expectations are then matched to Datastream price data as of the same day. Provided that earnings are positive, which happens in 97% of the firm-quarters in our sample, we compute E/P ratios.

Second, for vulnerable and nonvulnerable stocks separately, we aggregate data to the country-industry level by value-weighting stock-level earnings yields. Value-weighting uses each stock's market capitalization, following Bekaert et al. (2011). Industry classification is from ICB Level 3 data on Datastream. Thus, we obtain quarterly $\left(\frac{E}{P}\right)_t^{vulnerable}$ and $\left(\frac{E}{P}\right)_t^{non-vuln.}$ for each industry-country pair.

Third, to address the possibility that earnings yields are affected by stock characteristics other than country and industry membership, we introduce time differencing as follows. To all $\left(\frac{E}{P}\right)_t^{non-vuln.}$, we add the average difference between $\left(\frac{E}{P}\right)_t^{vulnerable}$ and $\left(\frac{E}{P}\right)_t^{non-vuln.}$ during the first ten observations of the sample period (June 2005 to September 2007). Because sovereign risk was negligible during that period, this adjustment term differences out any earnings yields differentials across firms that persist after removing country and industry effects. This makes sure these residual differentials are not spuriously attributed to sovereign risk. Finally, we compute VD_t for each country-industry pair as in Equation (3), and winsorize values at the 5% level.[14]

We obtain quarterly Q_t observations for each country as follows. The sovereign spread S_t is the ten-year euro-denominated sovereign CDS spread. The recovery rate R_t is from Markit's survey of CDS dealers. Such recovery rates are used by dealers to mark-to-market their positions, and to unwind CDS trades. The risk-free rate r_t is the yield on the benchmark ten-year German Bund minus the ten-year German CDS spread. The maturity of sovereign debt L_t is

[14] Not all country-industry pairs are populated. Some countries have no stocks in a given industry. Other countries do not have both vulnerable (*Vulnerability Score* $>$ 0) and nonvulnerable (*Vulnerability Score* = 0) stocks in the same industry, so a value discount cannot be defined.

Table 6
How costly is sovereign default?

Panel A: Summary statistics

	$(E/P)_{non-vuln.}$	VD	Q	S	R	r
Mean	0.092	0.018	0.097	0.010	0.396	0.028
Median	0.079	0.034	0.048	0.004	0.400	0.030
Std. Dev.	0.086	0.317	0.144	0.035	0.021	0.012
N	2,278	2,278	2,278	2,278	2,278	2,278

Panel B: Structural valuation model

	VW E/P	Median E/P	VD non-winsorized	GIIPS only
K_0 (Cost of default)	0.0127***	0.0167***	0.0094***	0.0166***
	(4.99)	(6.33)	(4.93)	(2.64)
K_1	0.292**	0.389***	0.218***	0.477***
	(4.29)	(7.02)	(2.82)	(2.71)
Corr(VD^{fitted}, VD)	0.41	0.42	0.34	0.37
N (country-industry-quarter)	2278	2278	2278	855

The value discount (VD) and the earnings yield of nonvulnerable firms $(E/P)^{non-vuln}$ are defined at the country-industry-quarter level as described in the text. The risk-neutral default probability (Q) is computed from the sovereign spread (S), recovery ratio (R), and risk-free rate (r) as defined in the text. Data are from June 2005 to December 2013. Panel A reports summary statistics. Panel B has results of the maximum likelihood estimation of parameters K_0 and K_1 in the equation:

$$VD = \frac{K_0}{(\frac{E}{P})^{non-vuln.} + K_0} Q^{K_1} + \varepsilon$$

Standard errors are double-clustered at the country and time levels. T-statistics are reported in parentheses below the coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

equal to ten years, because we observe ten-year CDS spreads. All observations are lined up in time with VD_t and $\left(\frac{E}{P}\right)_t^{non-vuln.}$. Equation (1) yields Q_t given S_t, R_t, r_t, and L_t .

Table 6, Panel A, has summary statistics. There are 2,278 country-industry-quarter observations for which a value discount can calculated. The average earnings yield of nonvulnerable stocks $\left(\frac{E}{P}\right)_t^{non-vuln.}$ is 0.092, and the average value discount VD_t is 0.018. Note there is a lot of dispersion in VD_t, as indicated by a standard deviation of 0.317, while the dispersion in $\left(\frac{E}{P}\right)_t^{non-vuln.}$ is not that large compared with its average level. The average (bond-based) risk-neutral probability of default Q_t is 0.097, and its standard deviation is 0.144.

Table 6, Panel B, shows that the cost of sovereign default is expected to be large. There we report the results of estimating model parameters K_0 and K_1 by maximum likelihood. Standard errors are double-clustered at the country and date level. We find a cost of default K_0 equal to 1.27% per year in our baseline specification, statistically significant at the 1% level. That is, following sovereign default, vulnerable firms are expected to experience a large decrease in their long-run rate of earnings growth and/or a large increase in their cost of equity capital.

The following calculation provides additional perspective on the economic magnitude of the cost of sovereign default K_0. Because the average $\left(\frac{E}{P}\right)_t^{non-vuln.}$ is 9.2% per year, our K_0 estimate of 1.27% per year implies that sovereign default leads to a 12% (1.27/(9.2+1.27)) destruction in the value of vulnerable stocks' productive assets. To the best of our knowledge, ours and Jeanneret (2017) are the first estimations of the cost of sovereign default from stock market data.[15] These estimates may be useful in guiding quantitative models of sovereign debt (e.g., Arellano 2008; Borri and Verdelhan 2012) in their calibration of sovereign default cost parameters.

The K_1 estimate in Table 6 is equal to 0.292 with t-statistic equal to 4.29. That is, the relationship between VD_t and Q_t is strongly concave. Therefore, most of the value losses due to sovereign default materialize in asset prices at low or moderate levels of the risk-neutral default probability, that is, typically much before default actually takes place.

Panel B of Table 6 also shows that our basic conclusions are robust to alternative estimations. In the second column we report results in which earnings yields are aggregated differently. Each date we take the median across each country-industry pair instead of value-weighting. The cost of default estimate K_0 increases from 1.27% to 1.67% per year, and remains statistically significant at the 1% level. In the third column we do not winsorize the VD_t observations. The cost of default estimate K_0 decreases to 0.94% per year and remains statistically significant at the 1% level. However, model fit worsens: the correlation between fitted and observed VD_t drops from 0.41 to 0.34.

In the fourth column we restrict the data to GIIPS countries. The number of observations drops from 2,278 to 855 country-industry-quarters. The cost of default K_0 estimate increases from 1.27% to 1.67% per year. The parameter K_0 still is statistically significant at the 1% level. From the alternative estimations, we conclude that Panel B's result is broadly robust: stock prices behave as if sovereign default has an economically large impact on vulnerable firms.

4. Other Channels

The previous sections show that stocks are priced as if financial intermediation disruption and impaired government relationships are channels through which sovereign default is costly. In this section we explore two additional channels. We do not find cross-sectional evidence of a foreign exchange (FX) depreciation channel, or of an imported intermediate inputs channel.

[15] Jeanneret (2017) estimates that a sovereign default in Europe reduces the rate of economic growth by approximately 5% per year over a period of 2.5 years on average. This amounts to an (overall) economic contraction of approximately 12%.

4.1 FX devaluation

This channel operates through real exchange rate devaluation and currency mismatches in corporate balance sheets. Sovereign default is often associated with sharp real exchange rate depreciation (Reinhart 2002; Asonuma 2016). Such sharp devaluation could distress corporate balance sheets, to the extent that liabilities are denominated in strong currency and assets in devalued domestic currency (Du and Schreger 2015).

The euro sovereign crisis is a special case because defaulting countries are part of a monetary union. There are two basic issues: whether or not sovereign default triggers exit from the eurozone, and, in case it does, to what extent corporate liabilities denominated in euros would be redenominated to the newly (re)created domestic currency. In any event, however, the FX depreciation channel predicts that, all else equal, firms with a higher fraction of domestic sales, and firms with relatively more non-euro debt on their capital structure, are relatively worse off following sovereign default.

The dummy variables *High domestic sales* and *High foreign currency debt* capture cross-sectional variation on the exposure to redenomination risk. *High domestic sales* flags firms in the top tercile of domestic sales each year. From FactSet Revere we obtain the fraction of domestic sales for each firm-year in our sample. On average across all data, 33.1% of sales are domestic. From Capital IQ we obtain the currency distribution of liabilities for each firm in each year.[16] The dummy variable *High foreign currency debt* flags firms whose non-euro debt consists of 10% or more of their total assets. Across our sample, the average of *High foreign currency debt* is 0.066.

We test whether *High domestic sales* and *High foreign currency debt* stocks are more sensitive to changes in redenomination risk using two approaches. First, we assume that the probability of euro exit conditional on sovereign default is constant over time. In that case, changes in sovereign spreads proxy for changes in redenomination risk. Then we can assess the FX devaluation channel by testing whether stocks with *High domestic sales* and *High foreign currency debt* have higher sensitivity to sovereign risk changes (Δ *Spread*). Results are in Columns (1) and (2) of Table 7.

In Column (1) of Table 7, the interaction term Δ *Spread* $\times$ *High domestic sales* is negative as predicted by the FX depreciation channel. However, the coefficient is economically small and statistically insignificant. Column (2) shows that, contrary to the FX depreciation channel, the coefficient on Δ *Spread* $\times$ *High foreign currency debt* is positive. It is, however, statistically insignificant. Untabulated regressions show these conclusions are unchanged if the sample is restricted stocks from the GIIPS countries, or when we focus on firms with *High domestic sales* and *High foreign currency debt* simultaneously.

16 We match 92% of our firm-month observations to FactSet Revere, first by SEDOL and then by name. We match 48% of our firm-month observations to Capital IQ by name.

Table 7
Is there evidence for FX devaluation or imported intermediate inputs channels?

Dependent variable:				Quanto		Corporate	
Excess stock returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Spread	−0.13***	−0.112***	−0.126***				
	(3.15)	(3.23)	(3.33)				
Δ Spread × High domestic sales	−0.008						
	(0.41)						
Δ Spread × High foreign currency debt		0.144					
		(0.92)					
Δ Spread × High intermediate input import ratio			−0.004				
			(0.12)				
Δ Redenomination risk				0.293	0.347	−0.705*	−1.154*
				(0.91)	(0.94)	(1.69)	(1.95)
Δ Redenomination risk × High domestic sales				0.059		0.779**	
				(0.67)		(2.15)	
Δ Redenomination risk × High foreign currency debt					3.43		0.059
					(1.17)		(0.06)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factors × Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factors × Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (stock-months)	83,833	43,159	90,909	53,327	25,441	41,013	18,108
R^2	0.236	0.255	0.222	0.231	0.258	0.206	0.239

The table has results of panel regressions of stock-level excess returns onto contemporaneous changes on sovereign spreads, or onto contemporaneous changes in redenomination risk. Redenomination risk is measured using either sovereign CDS quantos or corporate securities, as explained in the text. The sample consists of large non-financial eurozone firms. Data are monthly from July 2005 to December 2013. The dummy variable *High domestic sales* flags firms in the top tercile of fraction of domestic sales. Data are from FactSet Revere. The dummy variable *High foreign currency debt* flags firms with foreign currency debt above 10% of total assets. Data are from S&P Capital IQ. *High intermediate input import ratio* flags firms in the highest tercile of imported intermediate inputs, as explained in the text. Data are from OECD. Standard errors are clustered at the time level. T-statistics are reported in parentheses below the coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Our second approach to test the FX devaluation channel does not proxy for redenomination risk using sovereign spreads. Instead, it uses two direct measures of redenomination risk from the literature. De Santis (2015) uses CDS quantos—that is, differentials between dollar- and euro-denominated sovereign CDS spreads. He argues that the difference between a eurozone country's quanto and Germany's quanto measures that country's redenomination risk. Alternatively, Krishnamurty, Nagel, and Vissing-Jorgensen (2015) measure redenomination risk using the differential between euro-denominated CDS spreads of "safe" European corporations and the corresponding yield spreads of non-euro-denominated bonds from the same corporation. The correlation between the two measures (across countries and over time) is 0.24.[17] We evaluate the FX devaluation channel by testing whether firms with *High domestic sales* and *High foreign currency debt* display

[17] CDS quanto differential data is from Bloomberg and start on July 2008. We delete three massive outliers, all for Greece. The non-euro-denominated corporate bonds that are duration-matched to corporate CDS spreads (and to the corresponding risk-free term swap-curve) are Telefonica (USD, June 20, 2016) , EDP (GBP, August 9, 2017), EDF (USD, January 26, 2019), Eni (GBP, December 17, 2018), EON (GBP, January 27, 2014), Nokia (USD, May 5, 2019), KPN (USD, September 30, 2024), and Inbev (USD, January 15, 2019).

higher sensitivity to changes in redenomination risk according to the two redenomination risk measures. The results are in Columns (4) to (7) of Table 7.

In Columns (4) and (5) we find that, contrary to the FX devaluation channel, stock returns load positively on Δ *Redenomination risk* when such is defined using CDS quanto differentials. And the coefficients on the interaction terms with *High domestic sales* and *High foreign currency debt* are positive instead of negative. However, all coefficients are statistically insignificant.

In Columns (6) and (7) we find that stock returns do load negatively on Δ *Redenomination risk* when such is defined using the metric in Krishnamurty, Nagel, and Vissing-Jorgensen (2015). That is, on average, an increase in redenomination risk is associated with lower stock returns. However, such result is not robust. In untabulated regressions we find it does not hold in the subsample of GIIPS countries. Moreover, Columns (6) and (7) show that stocks with *High domestic sales* and *High foreign currency debt* are not more sensitive to redenomination risk as hypothesized.

In sum, we do not find cross-sectional evidence supporting the FX depreciation channel using either of our approaches.

4.2 Imported intermediate inputs

Mendoza and Yue (2012) propose that sovereign default is costly because it reduces the economy's productive efficiency. Specifically, sovereign default would be associated with forced reallocation of production away from imported intermediate products toward domestic intermediate inputs. This channel implies that stocks with a higher fraction of imported intermediate inputs should be more sensitive to sovereign risk.

To test the channel, we obtain industry-country level data on intermediate input imports from OECD.Stat. The STAN Input-Output Import Ratio contains the fraction of total intermediate demand that corresponds to imported intermediate inputs. We manually match STAN's industry classification to ICB Level 3 classification, and attribute to each stock its country-industry's intermediate input import ratio. The dummy variable *High intermediate input import ratio* flags stocks in the top quintile each month. Across all observations in our sample, the average *High intermediate input import ratio* is 0.206.

Column (3) of Table 7 shows that we do not find cross-sectional evidence supporting the Intermediate Input Imports channel. The interaction term Δ *Spread* × *High intermediate input import ratio* is negative, consistent with the proposed channel. However, the coefficient is small and statistically insignificant. In untabulated regressions we verify that conclusions are unchanged if *High intermediate input import ratio* is defined based on top tercile instead of top quintile of stocks, or if the sample is restricted to stocks from the GIIPS countries. That is, we find no evidence that stocks in sectors with heavy use of imported intermediate inputs have larger sensitivity to sovereign risk.

The lack of cross-sectional evidence for the two aforementioned channels does not necessarily imply they are irrelevant in general. The foreign-exchange depreciation and intermediate input channels may operate in emerging market sovereign crises for example. And it is possible that our lack of cross-sectional evidence is due to lack of cross-sectional variation in the exposure to these channels in our stock sample.

5. Conclusion

This paper uses stock market data to examine the prospective costs of sovereign default. We study large nonfinancial firms in the eurozone from July 2005 to December 2013, a period that includes the euro sovereign crisis. First, we test cross-sectional implications of theories of sovereign default. We find support for theories of sovereign debt proposing that disruption in domestic financial intermediation is an important cost of sovereign default (e.g., Gennaioli, Martin, and Rossi 2014). Specifically, firms more vulnerable to credit market disruption have higher stock return sensitivity to changes in sovereign credit spreads. We also find that firms more exposed to the government have higher sovereign risk sensitivity. This is consistent with theories in which sovereign default is costly because it impairs private-sector relationships with the government (e.g., Cole and Kehoe 1998). While our results are consistent with Gennaioli, Martin, and Rossi (2014) and Cole and Kehoe (1998), we cannot completely rule out alternative interpretations of our findings.

We also estimate a structural valuation model to estimate the cost of sovereign default implicit in market prices. The model fits and extrapolates the empirical association between sovereign spreads and valuation ratio differentials. Model estimation indicates that the long-term cost of sovereign default on vulnerable firms is expected to be economically large. Specifically, stocks are priced as if sovereign default leads to a decline in the rate of long-term earnings growth coupled with an increase in the cost of equity capital adding up to 1.27% per year. This translates to a 12% destruction on the value of vulnerable firms' productive assets upon default. This estimate is based on publicly traded firms, and as such it is a lower bound for the overall economy because private firms are likely to be more vulnerable to financial intermediation disruption than public ones.

Our valuation approach concerns market expectations about the costs of sovereign default. These expectations need not be correct. This is why scrutinizing actual default episodes can shed additional light on the economics of sovereign debt and default. In particular, future research may examine whether default in fact has lasting effects on domestic credit disruption and private-sector relationships with the government.

Appendix A: Sovereign Beta Decomposition

In Section 3 we find that vulnerable firms have higher sensitivity to sovereign risk. This Appendix further examines such sensitivity by decomposing sovereign risk betas into an immediate and a long-term component. The immediate component is related to earnings expectations over the nearest three years. The long-term component is associated with three-year forward P/E ratios, and hence with long-term earnings growth and/or the cost of equity capital. We find that the higher sovereign risk sensitivity of vulnerable firms derives exclusively from the long-term component. That is, vulnerable firms' near-term earnings expectations are not more sensitive to sovereign risk. This result validates our Section 4 approach, as it shows that vulnerable firms' higher sovereign risk sensitivity do not reflect market concerns about near-term earnings, but concerns about long-term earnings growth and/or cost of equity capital. Therefore, the association between P/E ratio differentials and the risk-neutral probability of default contains information about long-term earnings growth and/or cost of equity capital conditional on sovereign default.

We first decompose stock returns excluding dividends into changes in short-term (up to three years) earnings expectations (E) and changes in P/E ratios computed using such earnings expectations (i.e., changes in three-year forward P/E ratios). Then we separately regress each change onto contemporaneous changes in sovereign spreads. The following notation helps. Denote E_t as earnings-per-share (EPS) expectations at time t. We can rewrite stock returns (excluding dividends) as:

$$\frac{P_{t+1}}{P_t} = \frac{P_{t+1}}{E_{t+1}} \frac{E_{t+1}}{E_t} \frac{E_t}{P_t} = \frac{\frac{P_{t+1}}{E_{t+1}}}{\frac{P_t}{E_t}} \frac{E_{t+1}}{E_t} \tag{A1}$$

Taking logs on both sides, assuming earnings expectations are positive, yields:

$$\log\left(\frac{P_{t+1}}{P_t}\right) = \left[\log\left(\frac{P_{t+1}}{E_{t+1}}\right) - \log\left(\frac{P_t}{E_t}\right)\right] + [\log(E_{t+1}) - \log(E_t)] \tag{A2}$$

Equation (A2) shows that log price changes can be decomposed onto changes in log P/E ratios and changes in log earnings expectations. Thus, if a firm's stock return is sensitive to sovereign

Table A1
Do firms with high external finance dependence have higher sovereign risk betas?

Dependent variable: Excess stock returns	
Δ Spread	−0.108***
	(2.79)
Δ Spread × High EF dependence	−0.070***
	(2.83)
High EF dependence	0.001
	(0.89)
Factors	Yes
Factors × High EF dependence	Yes
N (stock-months)	90,928
R^2	0.222

The table shows results of panel regression of stock-level excess returns onto contemporaneous changes on sovereign spreads (Δ *Spread*) and four-factor returns. *High EF dependence* is a dummy variable flagging firms with external finance dependence in the highest tercile in a given month. Data are from Claessens and Laeven (2003). Standard errors are clustered at the time level. T-statistics are reported in parentheses below the coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A2
Do vulnerable firms have higher sovereign risk betas? (Alternative stock-level specifications)

Panel A

	Vulnerability score = 0	Vulnerability score = 1, 2	Chi-square statistics (*p*-value)	Government exposure = 0	Government exposure = 1	Chi-square statistics (*p*-value)
Median $\beta_{\Delta \text{Spread}}$ (N time-series regressions per group)	−0.004	−0.137	**4.73**	0.017	−0.199	**9.92**
	[N = 731]	[N = 602]	(0.030)	[N = 905]	[N = 428]	(0.002)
$\beta_{\Delta \text{Spread}}$ (one panel regression per group)	−0.102***	−0.161***	**5.81**	−0.096***	−0.180***	**7.59**
	(2.59)	(4.28)	(0.016)	(3.07)	(3.30)	(0.006)

Panel B

Dependent variable: $\beta_{\Delta \text{Spread}}$ (time-varying per stock with one year of weekly data)	European factors			European & local factors		
		GIIPS only	2010–2013		GIIPS only	2010–2013
	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerability score	−0.091***	−0.057**	−0.070***	−0.178***	−0.215***	−0.13***
	(4.19)	(2.08)	(3.82)	(3.21)	(3.04)	(3.06)
Government exposure	−0.055*	−0.092**	−0.076***	−0.199**	−0.156*	−0.161***
	(1.88)	(2.47)	(3.16)	(2.79)	(1.71)	(2.87)
Time fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N (stock-weeks)	318,159	96,302	162,926	318,159	96,302	162,926
N (stocks)	1,298	413	1,097	1,298	413	1,097

The first line of Panel A reports median $\beta_{\Delta \text{Spread}}$ estimated from a full-sample regression of monthly stock returns onto contemporaneous changes in sovereign spreads (Δ *Spread*) and the four European stock factors. Stocks are grouped according to *Vulnerability score* or *Government exposure*. The second line of Panel A reports betas estimated from a SURE regression of monthly data and stocks grouped according to *Vulnerability score* or *Government exposure.* Chi-square statistics testing beta differences across the groups are reported. Panel B reports results of median regressions of $\beta_{\Delta \text{Spread}}$ onto *Vulnerability score* and *Government exposure.* These betas are estimated at the individual stock level from rolling regressions with one-year of weekly data. In addition to contemporaneous changes in sovereign spreads (Δ *Spread*), the regressions from which $\beta_{\Delta \text{Spread}}$ are calculated also include stock return factors. We use either a four-factor model with European factors, or an eight-factor model with both European and local factors. Local factors are orthogonalized with respect to contemporaneous changes in sovereign spreads (Δ *Spread*). Weekly four-factor data are from Andrea Frazzini. Standard errors clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A3
Do vulnerable firms have higher sovereign risk betas? (Alternative country-level specifications)

	Vulnerability score				Government exposure			
	European factors		European & Local factors		European factors		European & local factors	
Dependent variable:	EW	VW	EW	VW	EW	VW	EW	VW
Long-short returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Spread	−0.062	−0.077	−0.063	−0.083	−0.076	−0.049	−0.084	−0.075
White	(2.84)***	(2.74)***	(2.76)***	(2.64)***	(2.60)***	(2.14)**	(2.83)***	(2.46)**
Driscoll Kraay	(3.73)***	(3.14)***	(3.79)***	(2.62)***	(3.78)***	(1.84)*	(3.35)***	(1.93)***
Time-clustered	(2.64)***	(3.11)***	(2.63)***	(2.88)***	(2.56)**	(2.11)**	(2.75)***	(2.53)***
Factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (country-months)	1,094	1,094	1,094	1,094	1,094	1,094	1,094	1,094

The table shows regressions of stacked country-level long-short portfolio returns on contemporaneous changes in sovereign spreads (Δ *Spread*). Long-short portfolios within each eurozone country are based on *Vulnerability score* or *Government exposure*. Portfolios are value weighted, and consist of large nonfinancial eurozone firms. Data are monthly from July 2005 to December 2013. For each of the portfolio forming variables, we report results of three regressions: excluding four-factor returns, including four-factors returns, and including interactions of four-factor returns and country dummies. Below the coefficients, we report t-statistics based on three types of standard errors: White, Driscoll-Kraay (four lags), and time-clustered. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4
Decomposing sovereign risk betas

	Change in log prices		Change in log forward P/E ratios		Change in log EPS expectations				
	(1)	(2)	(3)	(4)	(5) Dropping negatives	(6) Dropping negatives	(7) Scaling by initial price	(8) Scaling by last price	(9) Scaling by aver. price
Δ Spread	−1.303***	−1.177***	−1.095***	−0.961***	−0.208**	−0.217*	−0.023**	−0.066*	−0.023**
	(3.40)	(2.97)	(3.50)	(3.22)	(2.09)	(1.68)	(2.00)	(1.95)	(1.99)
Δ Spread × Vulnerability score		−0.27***		−0.287***		0.017	0.004	0.016	0.004
		(3.13)		(4.15)		(0.19)	(0.45)	(0.50)	(0.50)
Vulnerability score		−0.006*		−0.002		−0.004	0.000	−0.002	0.000
		(1.91)		(0.67)		(1.32)	(1.18)	(1.10)	(1.12)
Constant	0.000	0.002	0.005	0.006	−0.005	−0.003	0.001	−0.003	0.000
	(0.05)	(0.31)	(0.62)	(0.76)	(1.04)	(1.32)	(1.26)	(1.47)	(0.57)
N (stock-quarters)	25,660	25,660	25,660	25,660	25,660	25,660	26,353	26,353	26,353
R^2	0.087	0.087	0.036	0.037	0.001	0.002	0.001	0.001	0.001

The table shows results of panel regressions that decompose sovereign risk betas. Data are quarterly from 2005 to 2013. As in Appendix A, firm-level log price changes are decomposed into changes in log EPS expectations (averaging EPS expectations over the nearest three years) and changes in log P/E ratios based on such EPS expectations. In the first six columns, log price changes and its components are separately regressed on changes in sovereign spreads, including interactions with *Vulnerability score*. In this column, observations with negative earnings expectations are dropped. Columns (7) to (8) have results of panel regressions of changes in EPS expectations (using average EPS expectations over next three years) scaled by stock prices, using three types of price scalings. Standard errors are clustered at the country-time level. *T*-statistics are reported in parentheses below the coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

spread changes, it must be because its earnings expectations, or its P/E ratio, or both, are sensitive to spread changes.

Appendix Table A4 contains the results from decomposing sovereign risk sensitivity into changes in P/E ratios and changes in earnings expectations. As in Section 4, we use quarterly mean EPS expectations from I/B/E/S for up to three years. Because the decomposition in Equation A1 requires positive earnings, we delete observations with negative earnings, which reduces the sample (firm-quarters) by just 3%.

Columns (1) and (2) report regressions of changes in log prices onto Δ *Spread*. Note that these columns simply reproduce baseline results from Table 2A with the following four changes. We use changes in log prices instead of stock returns on the left-hand side, use quarterly instead of monthly data, focus on the subset of firms for which we have I/B/E/S data, and exclude four-factor returns. Column (2) shows that the interaction term Δ *Spread* × *Vulnerability score* is negative and statistically significant. That is, consistent with Panel A of Table 2, firms more vulnerable to financial intermediation disruption display higher sensitivity to sovereign risk.

Columns (3) and (4) report regressions of log P/E ratios changes onto Δ *Spread*. Columns (5) to (6) have regressions of changes in log short-term earnings expectations onto Δ *Spread*. Because changes in log P/E ratios and changes in log earnings expectations add up to changes in log prices (Equation 1), the regression coefficients also add up. That is, the coefficients in Column (1) are algebraically identical to the sum of the corresponding coefficients in Columns (3) and (5). Analogously, Column (2) coefficients are the sum of coefficients in Columns (4) and (6). Note that the coefficients on Δ *Spread* are significantly negative in both Columns (3) and (5). That is, as sovereign spreads increase, short-term earnings expectations are revised downward and stocks become "cheaper" in terms of three-year forward P/E ratios.

Importantly, however, the interaction term Δ *Spread* × *Vulnerability score* is negative and statistically significant in Column (4) but not in Column (6). Therefore, the short-term earnings expectations of vulnerable firms do not display higher sensitivity to sovereign spread changes. These firms' stock returns display higher sovereign risk betas entirely because their forward P/E ratios are relatively more sensitive to sovereign spread changes. This shows that the higher sovereign risk beta of vulnerable firms reflects higher sensitivity of market expectations about long-term (beyond three years) earnings growth and/or the cost of equity capital.

Columns (7) to (9) show that our dropping of negative earnings forecasts does not influence the key conclusion from Column (6). The left-hand-side variable is quarterly change in EPS expectations ($E_{t+1} - E_t$) without dropping negative earnings forecasts. These changes are scaled by stock prices in three different ways, all of them deliberately shutting down time-series variations due to price changes. We scale earnings either by the first, the last, or the average observed stock price in the matched sample. Regardless of how earnings expectations changes are scaled, we find that the interaction term Δ *Spread* × *Vulnerability score* is economically small and statistically insignificant.

Thus, the higher sovereign risk beta of vulnerable firms reflects not short-term (below three years) earnings expectations, but the fact that these firms' three-year forward P/E ratios are relatively more sensitive to sovereign risk, which indicates market concerns about the longer-term effects of sovereign risk.

Appendix B: Structural Model Proofs

Proposition 1. Consider riskless debt of a given vintage, paying $c > 0$ at an exponentially declining rate $m = \frac{1}{L}$. The value of this debt is:

$$B^{riskless} = E_t\left[\int_t^{\infty} e^{-r(s-t)} e^{-m(s-t)} c\, ds\right] = \frac{c}{r+m}. \tag{B1}$$

Let the value of sovereign debt be B_t. By definition, the sovereign spread S_t is such that $B_t = \frac{c}{r+S_t+m}$. On the other hand, by definition of the risk-neutral default probability, we must have:

$$B_t = \frac{c}{r+m} - Q_t(1-R)\frac{c}{r+m} \tag{B2}$$

Therefore from Equations (B1) and (B2) we get:

$$\frac{c}{r+S_t+m} = \frac{c}{r+m} - Q_t(1-R)\frac{c}{r+m} \tag{B3}$$

which solving for Q_t and using $m=\frac{1}{L}$ yields Equation (2) in the text:

$$Q_t = \frac{S_t}{(1-R)\left(S_t+r+\frac{1}{L}\right)} \tag{B4}$$

Proposition 2 (Formal Derivation). Take Equation (5) in Andrade (2009). Let *EM* and *DEV* denote vulnerable and nonvulnerable stocks, respectively. Let $\eta=0$, $r+\lambda\rho_x\overline{\sigma_x}=\overline{d}$, $\frac{\overline{c}}{c}=R$, and $\frac{\alpha}{\beta}=K_1$ to obtain:

$$\begin{aligned}\left(\frac{P}{E}\right)_t^{vulnerable} &= \frac{1}{(r+\lambda\rho_x\sigma_x-\mu_x)\left(\overline{d}-\overline{\mu_x}\right)}\\ &\times\left(\overline{d}-\overline{\mu_x}-\left[\frac{S_t}{(1-R)(S_t+r+m)}\right]^{K_1}\left[\overline{d}-\overline{\mu_x}+\mu_x-\overline{\mu_x}\right]\right)\end{aligned} \tag{B5}$$

Now substitute $\left(\frac{E}{P}\right)^{non-vuln.}=d-\mu_x \;\; =r+\lambda\rho_x\sigma_x-\mu_x$ and $K_0=\left(\overline{d}-d\right)+(\mu_x-\overline{\mu_x})$ in Equation (B5) to get:

$$\left(\frac{P}{E}\right)_t^{vulnerable} = \frac{1}{\left(\frac{E}{P}\right)^{non-vuln.}}\;\frac{\overline{d}-\overline{\mu_x}-\left[\frac{S_t}{(1-R)(S_t+r+m)}\right]^{K_1}K_0}{\left(\overline{d}-\overline{\mu_x}\right)} \tag{B6}$$

Therefore,

$$\frac{\left(\frac{P}{E}\right)_t^{vulnerable}}{\left(\frac{P}{E}\right)^{non-vuln.}} = 1-\left[\frac{S_t}{(1-R)(S_t+r+m)}\right]^{K_1}\frac{K_0}{\overline{d}-\overline{\mu_x}} \tag{B7}$$

Now note that $\overline{d}-\overline{\mu_x}=\left(\frac{E}{P}\right)^{non-vuln.}+K_0$. Substituting this in Equation (B7) gives:

$$\frac{\left(\frac{P}{E}\right)_t^{vulnerable}}{\left(\frac{P}{E}\right)^{non-vuln.}} = 1-\left[\frac{S_t}{(1-R)(S_t+r+m)}\right]^{K_1}\frac{K_0}{\left(\frac{E}{P}\right)^{non-vuln.}+K_0} \tag{B8}$$

Using the equation for Q_t in Proposition 1 and rearranging terms in Equation (B8) yields Equation (5) in the text.

Proposition 2 (Heuristic Derivation). To aid intuition, let's start reviewing the role of the bond-based risk-neutral probability of default Q_t in bond pricing. Let the value of a risk-free debt be denoted by $B^{riskless}$. The value of risky sovereign debt is:

$$B_t = B^{riskless}\left[1-(1-R)\,Q_t\right] \tag{B9}$$

Now consider an equivalent stock-based rather than bond-based equation. We will find the "stock-equivalent" of each of the objects B_t, $B^{riskless}$, $(1-R)$, and Q_t in the bond-based equation.

First, on the left-hand side of the equation we have the price of the vulnerable stock in place of B_t. Normalizing by earnings, the left-hand side has $\left(\frac{P}{E}\right)_t^{vulnerable}$. Instead of $B^{riskless}$, we have the price of the nonvulnerable stock, which, normalized by earnings, is $\left(\frac{P}{E}\right)^{non-vuln.}$.

Second, instead of the recovery rate upon default R, the stock-based equation has the price of the vulnerable stock at default divided by the price of the comparable nonvulnerable stock at default. Normalizing by earnings, the price of the vulnerable stock upon sovereign default is $\left(\frac{P}{E}\right)^{vulnerable} = \frac{1}{\overline{d}-\overline{\mu_x}}$. The normalized price of the comparable nonvulnerable stock is $\left(\frac{P}{E}\right)^{non-vuln.} = \frac{1}{d-\mu_x}$. Therefore, we obtain the ratio $\frac{d-\mu_x}{\overline{d}-\overline{\mu_x}}$ in place of R. Note that we can write:

$$\overline{d}-\overline{\mu_x}=d-\mu_x+\left(\overline{d}-d\right)+\left(\mu_x-\overline{\mu_x}\right)=\left(\frac{E}{P}\right)^{non-vuln.}+K_0 \tag{B10}$$

After some algebra, we get $\frac{K_0}{\left(\frac{E}{P}\right)^{non-vuln.}+K_0}$ in the stock-based equation in place of $(1-R)$ in the bond-based equation.

Finally, we need to move from the bond-based risk-neutral default probability Q_t to a stock-based risk-neutral default probability. Andrade (2009) shows that raising Q_t to the power of $K_1>0$ (defined in Equation (4)) is the correct adjustment given model assumptions. That is, the stock-based equation has $Q_t^{K_1}$ in place of Q_t.

Collecting what we have thus far:

$$\begin{aligned}
&\textit{Bond Equation}: && B_t = && B^{riskless}\left[1-(1-R)\,Q_t\right]\\
&\textit{Stock Equation}: && \left(\frac{P}{E}\right)_t^{vulnerable} && =\left(\frac{P}{E}\right)^{non-vuln.}\left[1-\frac{K_0}{\left(\frac{E}{P}\right)^{non-vuln.}+K_0}Q_t^{K_1}\right]
\end{aligned}$$

Rearranging the *Stock Equation* gives Equation (5) in the text.

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