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'Too central to fail' firms in bi-layered financial networks: linkages in the US corporate bond and stock markets

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Several measures have been recently developed in the financial networks literature to quantify the vulnerabilities of firms in specific markets for risk management. However, firms are often active in multiple asset markets simultaneously with potentially different degrees of vulnerabilities across markets. One can hypothesize that since assets are backed by similar firm-level fundamentals, the vulnerability measures across markets would be highly correlated. In this paper, we present two results based on the empirical correlation of network-based measures of vulnerabilities by studying US firms' asset returns that are active in stock as well as corporate bond markets. First, the magnitude of the relationship, while positive and significant, is not very large. Quantitatively, a unit percent increase in vulnerability measure of a firm in the stock market is associated with 0.15% increase in the vulnerability in the bond market. Second, the vulnerability of the firms in the stock market is negatively related to firm size proxied by market capitalization, indicating that 'too-big-to-fail' firms tend to be 'too-central-to fail'. By adopting instrumental variables, we show that the coefficient has a higher magnitude. The results are robust with respect to choices of asset classes, maturity horizons, model selection, time length of the data, as well as controlling for return sensitivities to market-level factors.

Keywords: Network centrality; Risk management; Vulnerability; Stocks and bonds; Too central to fail

JEL Classifications: G01, G32, G17, G18

1. Introduction

In the aftermath of the 2007–2009 financial crisis, interconnectedness in the economic and financial systems has come under scrutiny as one of the leading potential mechanisms for diffusion of distress from a local neighborhood of the epicenter, leading to a system-wide impact. The nature and degree of connectedness within a network influence the chances of containment of a shock and chances of distress spillover arising out of a localized, idiosyncratic shock. The role of interconnectedness became very apparent in the theory and practice of macroprudential regulations. *The Financial Crisis Inquiry Report* (2010) noted the role of financial linkages in the spillover of distress, stating that:

> Without the bailout, AIG's default and collapse could have brought down its counterparties, causing cascading losses and collapses throughout the financial system.

The episodes of large-scale financial distress brought forward a theme of inquiry, namely, how to identify vulnerable firms that might act as epicenters of distress, and limit the damages? Three major themes have evolved to collectively address resilience and/or vulnerabilities of firms in the form of *Systematically Important Firms* or SIFs: too big to fail, too connected to fail and too central to fail firms within a single network.

However, more often than not, firms are embedded in more than one network with different sets of interconnections leading to different sets of SIFs, which possess different degrees of vulnerability across markets. For management of risks, a crucially important question is whether a firm that is vulnerable in one network is also vulnerable in other networks? Although

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there have been some recent attempts to quantify the relationship between multiple levels of interconnectivity (e.g. Perillo and Battiston 2018), the nature of the relationship between vulnerabilities across networks remains largely unexamined. Thus interventions targeting specific firms (e.g. in the form of bail-outs) have often been carried out by policy makers without a complete mapping of linkages across markets.

In this paper, we ask the following questions: Are measures of the vulnerability of firms correlated across markets? If yes, what is the magnitude of the correlation? To answer these questions, we construct a flexible measure of firm-level vulnerability from interlinkages inferred from the asset return data and systematically analyze the relationship between vulnerabilities across markets. Our measure of vulnerability is based on a graph-theoretic construct from the dynamic relationship between assets, which we utilize in a standard econometric framework in the form of instrumental variable regressions to quantify the linkage across markets.

Specifically, we construct two layers of financial networks based on time series of stock returns and bond returns of a fixed set of firms. A visual example is demonstrated in figure 1. Based on a network measure of vulnerability, we estimate *ranks* of firms in the two asset return networks where a higher rank indicates higher vulnerability. Our main result is that the vulnerabilities of firms in the bond network are positively correlated with the vulnerabilities of firms in the stock network, although the coefficient of the relationship is not too large (but it is statistically significant). This finding is robust with respect to a large variety of controls (inclusive of the responsiveness of the bond returns to money market factors, short and long term on-off spread, Cochrane-Piazessi factor, term spread and default spread), time horizons and types of assets.

We hypothesize firm size to impact vulnerability negatively and instrument vulnerability in the stock market by the corresponding market capitalization. Qualitatively similar results prevail, and two new features emerge. One, the instrumental variable regression shows that the estimated coefficient is larger. Two, the first stage regression results are consistent with the hypothesis that firms with high market capitalization would exhibit low vulnerability in the stock market. This indicates that *too big too fail* firms tend to be *too central to fail*. Finally, we apply non-parametric clustering techniques borrowed from machine learning literature to complement and bolster the above analysis.

With the summary of the results as above, let us elaborate the methodology and the underlying theoretical layout. Yun *et al.* (2019) describe three concepts, namely, too big to fail, too connected to fail and too central to fail, in the context of systematically important financial institutions. The literature has also generally considered risk spillovers between financial institutions (e.g. Markose *et al.* 2012, Battiston *et al.* 2012b). However, given our econometric approach to the networks construction without relying on balance sheet data, we generalize the measure to incorporate a broader set of firms. At the same time, we apply on the methodology to high-frequency financial return data rather than low-frequency balance sheet data that have typically been used in the literature. Thus the method is more general, directly employable on longitudinal data and it is able to capture firm-to-firm shock spillovers. These features also pertain to the vector autoregression-based method proposed by Diebold and Yilmaz (2015). However, they do not exploit the topology of the constructed network to characterize node-level properties (like vulnerability in the present context). Therefore, our methodology retains the useful features of the econometric construction of networks and also exploits the topological properties of the networks to create an index of vulnerability.

Next, we describe the market structure. While it would be natural to expect vulnerabilities across markets to be positively related, it is difficult to hypothesize a priori about the corresponding magnitude. At the outset, we note that stock and bond prices for the same firms do not exhibit any stable relationship even though equity and debt are claims on the same fundamentals of the firms. One might conjecture that they should reflect the same or at least very similar information. As it turns out, that is empirically unfounded. A series of studies of time series properties of stock and bond prices and returns have established that the information content is very different and the correlation is quite unstable with changing signs (see Andersson *et al.* 2008 and references therein). Also, stock and bond markets are substantially different in terms of investor compositions and institutional features. Bai *et al.* (2019) described at least three dimensions along which these two markets differ, namely, investors risk appetite (bondholders would be more averse to downside risk than stockholders), firms' default risk captured by the bond issuance, and higher liquidity risk in the bond market. Bond markets are less liquid, dominated by institutional investors, and as a result, bond-implied risks factors diverge from the stock-implied ones. Thus while stock and bond prices of firms would be derived from the same set of fundamentals, given the differences in the market structures, institutional features and traders' compositions, it is difficult to theorize about the magnitude of the relationship between vulnerabilities, although the direction can be expected to be positive.

Our baseline dataset contains monthly data spanning over 71 months from February 2013 to December 2018. The bond price data is obtained from the TRACE database and the stock price data has been collected from the WRDS database. Since not all firms issue both bonds and stocks, we select only those active in both markets. Also, to maintain parity over maturity periods, we have considered bonds with a 10-year maturity period, which constitute typically a highly liquid market. Our dataset contains 282 such firms with matching characteristics in the baseline specification along with matching data for control variables (details explained in data description in section 2).

For constructing the network linkages, we follow the literature on *Granger Causal Networks* (Billio *et al.* 2012, Yun *et al.* 2019) which is constructed from bi-variate Granger-causality tests between all pairs of firms. We define vulnerability by calculating PageRank centrality (Page *et al.* 1999), which accounts for both the number and quality of inbound links that each node has, and quantifies the degree of *openness* of a given node to its neighbors, neighbors of neighbors and so forth. This quantification has been proposed in recent work by Yun *et al.* (2019), which builds on prior work by Billio *et al.* (2012). Notably, Billio *et al.* (2012) used eigenvector centrality as the primary pan-network measure of centrality

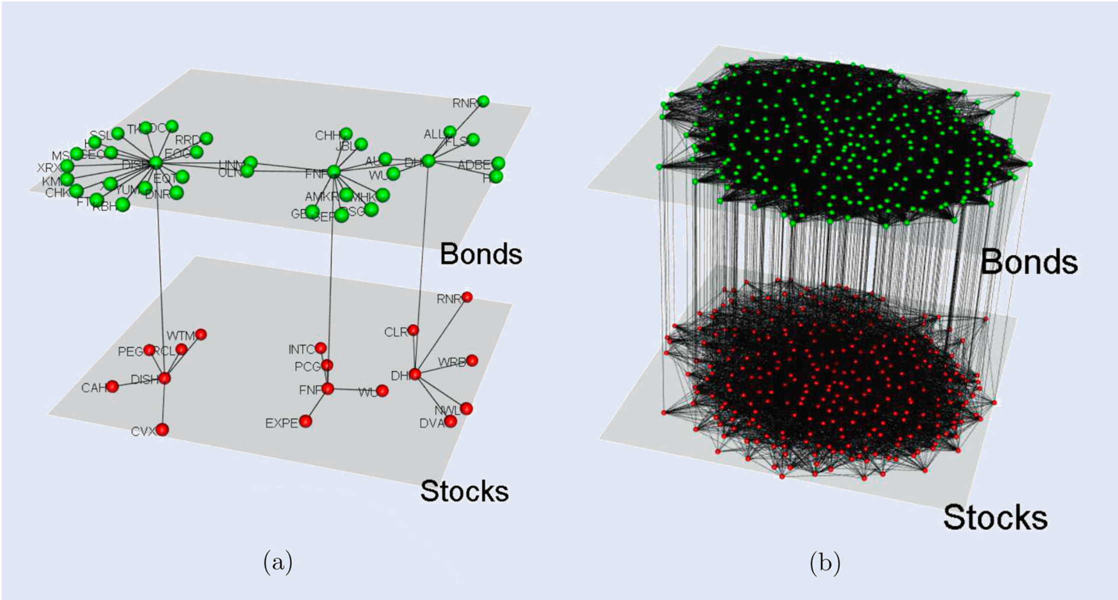

Figure 1. Panel (a): Illustrative example of multiplex network with three nodes belonging to both layers (firm identifiers are DISH, FNF and DHI; full set of firm ids are available in table A1 in the appendix). The rest of the nodes represent first-order neighbors of these three nodes that belong to the full sample of 282 firms considered in the baseline model. Panel (b): Multiplex network of the full sample comprising 282 firms active in both equity and debt markets.

based on spectral decomposition. PageRank is based on a transformation of eigenvector centrality that captures the in-degrees, which is important for quantifying *vulnerability* in the context of risk and also allows for tuning of dampening effects arising out of local and global neighborhoods in the network. In the robustness section, we provide the correlations of the PageRank measure with other network measures. Measures like eigenvector centrality and in-degree centrality are highly correlated with PageRank of the financial networks, which is intuitive since both capture the idea of vulnerability on the Granger causal network. Thus our results are robust to the choice of the centrality measure.

Our main regression model effectively captures the correlation between vulnerabilities in the stock and bond markets based on financial return data. However, financial returns are endogenous, leading to the scenario that both vulnerability measures are potentially endogenous. In order to analyze the relationship with respect to the exogenous firm-level fundamentals, we exploit firm-level stock market capitalization as an instrumental variable. This is motivated by two observations. First, size is a firm-specific variable that is determined in isolation, whereas centrality-driven vulnerability measure is network-dependent by construction. Second, size plays an important role in targeted interventions as an index of influence, as captured by the remark of Steven Rattner† :

> Without government intervention, GM and Chrysler would have shut down and liquidated. . . GM was *too big, too important* to let collapse.

Utilizing the instrumental variable regression, we see that the estimated coefficient is consistent in sign and significance with the main regression model. Additionally, we control for firm-specific variables that capture responsiveness to market sentiments, the volatility index (or *fear* index as it is popularly known) as well as liquidity factors. We see that responsiveness of firms to market sentiments, spread and liquidity do not seem to play an important role in influencing vulnerability in the bond market.

A comparison between our measure and existing measures of systemic risk like CoVaR (change in the Value at Risk Conditional on being under distress; proposed by Adrian and Brunnermeier 2016) and MES (marginal expected shortfall; proposed by Acharya *et al.* 2017) shows that the indices of systemic risk and the index of vulnerability do not convey the same information, a finding consistent with Yun *et al.* (2019). Finally, we use k-means clustering borrowed from machine learning literature (James and Witten 2013) which is non-parametric in nature, to characterize the relationship. This analysis also corroborates the mapping between stock and bond networks.

This paper's contribution to the literature is threefold. The first one is of theoretical nature. We establish that vulnerability can be concurrently analyzed in multi-layered financial markets. We use the nascent literature of multi-layered networks in the context of financial networks. This literature is relatively less populated (see Kivelä *et al.* 2014 for a review). Recent work emphasizes new indices of systemic risk in multi-layered networks (Poledna *et al.* 2015) and information diffusion in investors' networks (Baltakys *et al.* 2018), credit networks across financial firms (Luu and Lux 2019) among others. Our work directly brings the analysis of vulnerability in the context of a multi-layered network signifying segregated asset classes where the information contents in the dynamics of those assets are largely different.

Second, our findings focus on identifying vulnerabilities in asset markets. This is important from the point of view of targeted intervention by central banks and other financial authorities to restore stability in the market during times of

† https://www.gsb.stanford.edu/insights/steven-rattner-2009-us-auto-bailout-was-necessary

crisis, where intervention on a chosen set of firms in one asset market can directly have spillovers in complementary asset markets. This finding adds to the growing literature of analysis of financial contagion and the role of central nodes in a financial network (Glasserman and Young 2016). The literature on mechanisms for identifying systematically important firms is extensive and consists of many different but complementary approaches. The background literature on mechanisms of spillovers due to the financial linkages range from insolvency spillovers (Eisenberg and Noe 2001, Gai and Kapadia 2010, Elliott *et al.* 2014), common exposure to liquidity shocks (Allen and Gale 2000), credit linkages (Battiston *et al.* 2012a) to informational channels (Acharya and Yorulmazer 2008, Ahnert and Georg 2018) among others. Based on the definition of DebtRank, Battiston *et al.* (2012b) show that only a small group of institutions were systematically important at the time of the financial crisis. Developments in the theoretical and simulation-based literature have shown that distress spillover can be widespread if not contained properly. Gai and Kapadia (2010), for example, show that the probability of a financial contagion can be very low; however, conditional on contagion occurring, there could be long cascading effects. Amini *et al.* (2016) show that institutions that have a large number of links and a large number of contagious links contribute most to the instability of a financial network. Our finding should resonate with the literature on networks inferred from time series data, in the line of work by Diebold and Yılmaz (2014) and Diebold and Yilmaz (2015). In the context of the connection between macroeconomic factors and financial market instability, our paper also relates to Diebold and Yilmaz (2008).

Finally, our finding establishes a linkage between the stock and bond markets. We note that return dynamics of bonds and stocks are known to be determined by generally different sets of factors. Fama and French (1992), Lin *et al.* (2014) and Fama and French (1993) find that except for low-grade bonds, there are few common determinants of returns in the two markets. Vassalou and Xing (2004) showed that default risk affects equity returns. However, the relationship is generally complicated and shows time-varying features (Connolly *et al.* 2005, Cappiello *et al.* 2006). As opposed to the above literature that typically analyzes dynamics of corporate equities and government-issued bonds, we analyze a set of firms that are active in both markets simultaneously and establish that the vulnerability components in both markets are related. As far as we know, this is a novel analysis in terms of linkage between networks constructed from different asset classes.

Rest of the paper is organized as follows. In section 2, we describe the data along with the procedure for sample selection. Next, we describe the construction of a measure of vulnerability using centrality measures on networks inferred from time series data. In section 3, we analyze the relationship between vulnerabilities of firms embedded in the stock return network vis-à-vis vulnerabilities of the same set of firms in the bond return network. All robustness checks have been presented in sections 4 and 5 describes the non-parametric analysis based on k-means clustering. Section 6 summarizes and concludes the paper.

2. Empirical data and construction of variables

This section provides a complete description of the data, methods used to construct the variables of interest and the methods used to analyze the relationship between bonds and stock networks. We denote the set of all firms in our sample by $\mathcal{N}$, a network by $\Gamma = \langle \mathcal{N}, \mathcal{W} \rangle$ where $\mathcal{N}$ also represents the set of nodes and $\mathcal{W}$ represents the set of connections among the nodes. We denote the number of firms in the set $\mathcal{N}$ by N. The corresponding adjacency matrix is denoted by W. In the case of the stock market, we utilize the notation W_s, and in case of the bond market, we use W_b.

2.1. *Data description: sample selection*

Here, we detail the steps taken in selecting the sample of stocks and bonds for analysis. We have used the services of TRACE† system for obtaining bond prices and the CRSP‡ database for stock prices, accessed through Wharton Research Data Services (WRDS).§ Stocks and bonds are chosen such that they are issued by the same firm ; hence, we have sampled only the firms that issue corporate bonds. For our baseline estimation, we collect daily price data on $N = 282$ stocks and bonds over the period of $T = 71$ months (February 2013 to December 2018) such that there is at least one data point per month for each stock and bond, and complete availability of the set of control variables (described in table 1) is ensured. Since averaging daily stock price over a month may suppress information content of fluctuations, we select the closing price of the first trading day of the month to convert the daily series into a monthly series.

Our analysis considers a wide variety of bonds, including plain bonds, senior notes, subordinated unsecured notes, senior subordinated unsecured notes, senior unsecured notes, senior bank notes, loan participation notes, subordinated notes, senior subordinated notes, senior secured bonds, junior subordinated notes, pass-through certificates, unsecured notes in the baseline model. These securities have variations in coupon types in terms of floating or fixed coupons. We consider additional classes along with different maturities of non-convertible bonds in our robustness checks. In our baseline specification, we have sampled bonds with a maturity period of 10 years, with maturity dates between 2017 and 2023. The main reason for considering bonds with 10 years' maturity period in our baseline model is that within the data, we observe that the 10-year bonds have been traded more frequently than others (shorter- and longer- term). In the section on robustness, we have considered bonds with less than 10 years and more than 10 years' maturity. All results hold.

In the following, we describe the computation of the return series from the price data and details of other variables used in our analysis. A summary of all the variables utilized in the paper, along with the corresponding sources, has been described in table 1.

† Website: https://www.finra.org/filing-reporting/trace
‡ http://www.crsp.org/
§ https://wrds-www.wharton.upenn.edu/

Table 1. Variable description.

Variable	Description
Bond market control variables	
CP 5-year forward rate factor	Cochrane and Piazzesi (2005) proposed a single return-forecasting factor that is a linear combination of forward rates or yields that explain the time-variation in the expected return of all government bonds. They find that the same factor predicts bond returns at all maturities. Lin *et al.* (2014) find that the CP 5-year forward rate factor has predictive power for corporate bond returns. We have used the daily treasury yield curve rates obtained from the US Department of the Treasury to estimate the forward rates through 1 to 5 years to obtain $\boldsymbol{f}_t$. Lin *et al.* (2014) have estimated $\hat{\boldsymbol{\gamma}}$ using Fama-Bliss zero-coupon bond prices from 1973 till 2010 for the forward rates. We have used the linear combination $\hat{\boldsymbol{\gamma}}^T \boldsymbol{f}_t$ as the CP factor.
$\Delta mmmf$	Monthly percentage changes in total money market mutual fund assets using data from the FRB
On-/off-spread (5-year)	Difference between 5-year constant maturity treasury bond yield and 5-year generic treasury rate reported by Bloomberg (USGG5YR) (see Pflueger and Viceira 2011)
On-/off-spread (10-year)	Difference between 10-year constant maturity treasury bond yield and 10-year generic treasury rate reported by Bloomberg (USGG10YR) (see Pflueger and Viceira 2011)
Term spread	Difference between 10-year constant maturity and 3-month constant maturity treasury bond yields obtained from Federal Reserve Economic Data
Default spread	Difference between average yields of AAA and BBB bonds. The series were obtained from Federal Reserve Economic Data.
Instrument variables	
Firm fundamentals	Market capitalization(*MCAP*), earnings-per-share (*EPS*) and dividends-per-share (*DPS*) of the sample of 282 firms are annual values collected from Compustat accessed through the WRDS data services
Fama-French Factors	Fama-French factors (monthly frequency) are collected through WRDS
CBOE Volatility Index (VIX)	Series of monthly frequency was obtained from Federal Reserve Economic Data
Baker-Wurgler Sentiment Index	The index is extracted from the daily data obtained from Jeffrey Wurgler's webpage[a]. The series is of monthly frequency obtained by selecting the data at the start of every month.
Pastor-Stambaugh Liquidity Indices	The indices are extracted from daily data of levels of aggregated liquidity, innovations in aggregated liquidity (non-traded liquidity factor) and traded liquidity factor daily series obtained from Lubos Pastor's webpage[b]. The series are of monthly frequencies obtained by selecting the data at the start of every month.

Note: The bond market control variables are derived from the variables described here as mentioned in section 2.4. With the exception of firm fundamentals, all the instrument variables are derived from the variables described here as mentioned in section 2.5: http://people.stern.nyu.edu/jwurgler, https://faculty.chicagobooth.edu/lubos-pastor/data.

2.2. *Return series construction*

Each bond/stock price is denoted by $\{p_{it}^{b/s}\}_{i\in N}$. Return series is defined as the first difference of the log price series:

$$r_{i,t}^b = \ln(p_{i,t}^b) - \ln(p_{i,t-1}^b) \quad \text{and} \quad r_{i,t}^s = \ln(p_{i,t}^s) - \ln(p_{i,t-1}^s) \tag{1}$$

for $i \in \mathcal{N}, t \in [1, 71]$ for each of the 71 months under consideration, beginning from February 2013 to December 2018. For the bond market, this is similar to the *clean price* approximation prescribed in Bessembinder *et al.* (2008).† The baseline regression consists of 282 firms (for details, see table A1 for which prices of stocks and bonds and the balance sheet variables are available for the entire period of study.

There is one issue that needs to be addressed with the bond market in our data. Some firms issue multiple types of bonds (see table A1). Therefore, we have to combine the corresponding multiple return series into one series so that we can uniquely define vulnerability for those firms in the bond market. Since we construct a single measure of vulnerability in the bond market, we take the first principal components of the set of bond returns issued by individual firms. For example, if a firm issues more than one bond (like Amgen Inc or Bank of America Corp in table A1), then we construct the first principal component from the corresponding bond return series. Since the first principal component would itself be only one time series, that time series represents the *average* bond return dynamics. We have checked that the results are robust to excluding those firms from the sample that issued more than one bonds or alternately taking the simple arithmetic average of returns. After establishing the baseline results, we enlarge the class of bonds considered along with variation in maturity periods in the section on robustness checks.

† In the return calculations from clean prices, we exclude accrued interest component of holding period returns for bonds following the standard practice in literature (see e.g. Ederington *et al.* 2015). As Bessembinder *et al.* 2008 pointed out, such exclusion does not affect the distributional properties of bond returns. Additionally, we note that we have not incorporated inflation in the return series construction, since when estimating Granger causality in the next step, the common inflation factor would become redundant.

2.3. *Measuring firm-level vulnerabilities from the stock and bond returns*

In this section, we define vulnerability following Yun *et al.* (2019), who interpreted the variable to capture the contribution to *systemic risk*. However, since we are not relating this measure to macroeconomic shock propagations in this work, we interpret the measure to capture *vulnerability*

Table 2. Summary statistics.

	N	Mean	Standard Deviation	Median	25th percentile	75th percentile	t-value
log (bond PageRank)	282	– 5.86322	0.64373	– 5.93348	– 6.32464	– 5.45754	– 153
log (stock PageRank)	282	– 5.85736	0.64231	– 5.88548	– 6.26148	– 5.44225	– 153
$\beta_{cp-factor}$	282	0.0042	0.00839	0.0056	0.00291	0.00752	8.40342
$\beta_{\Delta mmmf}$	282	– 0.00003	0.0001	– 0.00004	– 0.0001	0.00002	– 5.58187
$\beta_{on-off-spread-5years}$	282	0.10829	0.40685	0.10038	– 0.07754	0.26222	4.4698
$\beta_{on-off-spread-10years}$	282	– 0.21846	0.48939	– 0.22522	– 0.44024	– 0.04234	– 7.49623
$\beta_{term-spread}$	282	– 0.00625	0.01391	– 0.00823	– 0.0121	– 0.00326	– 7.54109
$\beta_{default-spread}$	282	– 0.00579	0.02807	– 0.00115	– 0.00583	0.00184	– 3.46543
$\beta_{Excess-return-factor}$	282	1.02229	0.48973	1.01259	0.72515	1.2957	35.0548
$\beta_{SMB-factor}$	282	0.09591	0.61731	0.04829	– 0.27417	0.36535	2.60911
$\beta_{HML-factor}$	282	0.35828	0.71076	0.2495	– 0.11491	0.71416	8.465
$\beta_{Aggregate-Liquidity}$	282	– 0.0108	0.31249	0.00584	– 0.14784	0.15866	– 0.58044
$\beta_{Innovations-in-Liquidity}$	282	– 0.00804	0.34836	– 0.00597	– 0.19916	0.17599	– 0.38777
$\beta_{Traded-liquidity-factor}$	282	– 0.04172	0.4107	– 0.0715	– 0.25821	0.10155	– 1.70599
$\beta_{sentiment}$	282	– 0.01208	0.07191	– 0.00732	– 0.05212	0.0326	– 2.82062
β_{VIX}	282	– 0.00112	0.00287	– 0.00058	– 0.00207	0.00054	– 6.52543
Dividends per share (2013)	282	1.19546	1.15707	0.895	0.39	1.7417	17.35
Dividends per share (2014)	282	1.35566	1.27374	1.045	0.5	1.96	17.8729
Dividends per share (2015)	282	1.41372	1.31697	1.135	0.515	2.01	18.0265
Dividends per share (2016)	282	1.49556	1.57814	1.145	0.4	2.17	15.9141
Dividends per share (2017)	282	1.52827	1.48245	1.2	0.4	2.25	17.312
Dividends per share (2018)	282	1.68728	1.7131	1.2775	0.46	2.48	16.5397
Earnings per share (2013)	282	3.81798	6.14634	2.645	1.49	4.68	10.4314
Earnings per share (2014)	282	3.96291	7.26178	2.85	1.51	4.87	9.16422
Earnings per share (2015)	282	2.92131	9.55651	2.4	1.06	4.6	5.13338
Earnings per share (2016)	282	3.78099	9.45703	2.29	0.81	4.84	6.71391
Earnings per share (2017)	282	4.85117	13.31261	2.95	1.25	5.32	6.11939
Earnings per share (2018)	282	4.66908	14.26368	3.27	1.21	5.93	5.49698
log(market capitalization) (2013)	282	16.5552	1.29112	16.5407	15.74551	17.37004	215.325
log(market capitalization) (2014)	282	16.6106	1.33462	16.6103	15.80744	17.3854	209.003
log(market capitalization) (2015)	282	16.5351	1.39236	16.565	15.72447	17.34851	199.425
log(market capitalization) (2016)	282	16.5974	1.39362	16.6793	15.80259	17.46187	199.996
log(market capitalization) (2017)	282	16.6991	1.43583	16.7737	15.92438	17.62096	195.305
log(market capitalization) (2018)	282	16.6586	1.47173	16.7182	15.90411	17.57944	190.079

instead. To construct the measure of vulnerability, we first need to define a *Granger Causal Network* or GCN henceforth. Upon construction of the matrix, a PageRank vector is defined to capture the vulnerability. Below we elaborate on the methodology.

2.3.1. Construction of granger causal network (GCN). We use bi-variate Granger causality test to create a directed network arising out of pairs of asset returns (Billio *et al.* 2012, Yun *et al.* 2019) using a bivariate vector autoregression estimation:

$$X_t = A_{11}(L)X_t + A_{12}(L)Y_t + \mathcal{E}_{X,t}$$
$$Y_t = A_{21}(L)X_t + A_{22}(L)Y_t + \mathcal{E}_{Y,t}, \qquad (2)$$

where the terms $A_{11}(L)$, $A_{12}(L)$, $A_{21}(L)$, $A_{22}(L)$ associated with time series X_t and Y_t are the lag polynomials of orders a_{11}, a_{12}, a_{21}, a_{22} respectively with lag operator L. The system has all distinct roots inside the unit circle and the errors $\mathcal{E}_{X,t}$ and $\mathcal{E}_{Y,t}$ are i.i.d. with zero mean and constant variance. We carry out a Wald test for Granger causality between X and Y.

In order to construct a Granger Causal Network (GCN) of one asset type (stocks or bonds), we consider an $N \times N$ fixed matrix W with all entries taking values in the set $\{0, 1\}$. We call this an adjacency matrix of an unweighted, directed graph. The interpretation is that for $i \neq j$, $\omega_{i,j} = 1$, if firm $i's$ return Granger-causes firm $j's$ return. For $i = j$, $\omega_{i,j} = 0$ by design (the results remain qualitatively unchanged even if we define $\omega_{i,j} = 1$). The GCN is obtained from the adjacency matrix W as a directed graph. We construct two GCNs by conducting pairwise estimation using equation (2) with a lag polynomial of order two with 5 % level of significance, for stocks and bonds, respectively.† In section 4, we discuss the robustness of the results when we relax the lag order choice.

2.3.2. Quantifying vulnerability via pageRank of GCN. After constructing the Granger causal networks in the bond and stock markets (i.e. after constructing the adjacency matrices W_b and W_s), we use the idea of PageRank of nodes in the corresponding graphs (Page *et al.* 1999) to arrive at a measure of vulnerability of an asset‡ (in the line of Yun *et al.* 2019).

† We have also checked robustness of the results with a more restrictive 1 % level of significance. The estimated GCN for the stock market has 277 nodes in the largest component (out of 282 nodes in baseline sample) and the estimated GCN for the bond market has 281 nodes (out of 282 nodes in baseline sample). Taking the common set of firms, all results still hold.

‡ See tables A9 and A10 in the appendix for an analysis of the correlation of PageRank with other well-known measures of network centrality. The correlations with in-degree and eigenvector

PageRank is a recursive centrality measure which assigns a score to each node in a network structure, signifying the relative importance of the node with respect to its topological properties, i.e. its position in the network (see Koschützki *et al.* 2005). Specifically, the *recursiveness* appears in the definition of PageRank that the PageRank of a node depends on the degree of the node, i.e. number of direct neighbors and the PageRanks of those neighbors.

Consider a network Γ of N assets where asset i is linked to a set of assets N^i, such that $\mathcal{N}^i \subseteq \mathcal{N}$. The PageRank of the i-th asset in the network with adjacency matrix W is defined as:

$$PageRank(i) = \frac{(1-d)}{N} + d \sum_{j \in \mathcal{N}^i} \hat{\omega}_{ij} PageRank(j), \qquad (3)$$

where $i \neq j$, d is the dampening factor† and $\hat{\omega}_{ij} = \frac{\omega_{i,j}}{\sum_k \omega_{k,j}}$ is the degree-normalized weight associated with the number of outgoing links from node $j \in \mathcal{N}^i$ to node i.

In our case, the network is produced by Granger causality, i.e. ω_{ij} denotes Granger causality from asset i to j as defined above in section 2.3.1. An asset i is more vulnerable than j if $PageRank(i) > PageRank(j)$. Since the existence of an outgoing link from asset j to i means that the return of asset i is affected by the return of asset j, a vulnerable asset would be such that its returns are affected by a larger number of assets and/or its return is explained by other vulnerable assets.

2.4. Bond market control variables

In this section, we list the variables used in constructing control variables to explain the variation in bond PageRank through the variation in stock PageRank. Since we have derived the PageRank from returns, we expect that the PageRank could be explained by factors presented in the literature, that affect the predictability of bond returns. Lin *et al.* (2014) have found that corporate bond returns are more predictable than stock returns and the returns tend to be more predictable for short-maturity bonds. They find that Cochrane and Piazzesi (2005) factor (CP forward rate factor), liquidity factors like changes in percentage changes in total money market mutual fund assets ($\Delta mmmf$) have predictive power for corporate bond returns. They have used several forecasting variables for examining the predictability of corporate bond returns.

The set of variables used in this study include term spread, default spread, on-/off-the-run spread, CP 5-year forward rate factor. We estimate the coefficients in the following specification of the cross-section of returns.

$$\begin{aligned} &Bond\ returns_{it} \\ &= \beta_0 + \beta_i Y_t + \epsilon_{it}, \quad i = 1, \ldots, N;\ t = 1, \ldots, T \qquad (4) \end{aligned}$$

where Y represents the explanatory variables considered, β_i represents the sensitivity of returns with respect to the variables. In this setup, we estimate $\beta_{\Delta mmmf}$, $\beta_{on-off-spread-5years}$, $\beta_{on-off-spread-10years}$, $\beta_{cp-factor}$, $\beta_{term-spread}$ and $\beta_{default-spread}$ for a cross-section of $N = 282$ firms in the baseline specification. These computed values of the coefficients are used as control variables while explaining bond PageRank. Description of the explanatory variables used in place of Y is given in table 1 along with data sources.

2.5. Instrumental variables for vulnerabilities in the stock market

In the following, we construct instrumental variables for the stock market vulnerabilities used in our analysis. The main idea is that size can be expected to provide resilience against external shocks and hence larger firms may exhibit less vulnerability, implying that 'too big to fail firms' should also be 'too central to fail' firms. We exploit this idea using size variable as the main instrument for (the negative of) vulnerability. An obvious candidate for the size variable is the total assets of the firm. However, that is problematic due to lack of exogeneity in the sense that there is no a priori reason as to why total assets would impact either the bond market or the stock market more than the other in a systematic way.

Therefore, we consider stock market capitalization as an instrument, which by construction should more directly impact stock market vulnerability and the impact on bond market would be through the size effect via stock market.‡

Specifically, we have considered firm-level fundamentals such as market capitalization as a proxy for size,§ earnings and dividends per share as proxies for profitability, and sensitivities of the firm's stock returns with respect to the three Fama-French factors, CBOE volatility index (VIX), Baker-Wurgler sentiment index and Pastor-Stambaugh liquidity index as instruments for stock PageRanks.

It is well known that cross-section of stock returns are explained by the three Fama-French factors (Fama and French 1992, Petkova and Zhang 2005), indices like the Volatility Index or VIX created by Chicago Board Options Exchange (CBOE),¶ Baker-Wurgler sentiment index,‖ and

centrality is quite high, indicating that PageRank captures the vulnerability while simultaneously retaining the mathematical structure of eigenvector centrality.

† In the original work of Brin and Page 1998, a dampening factor of 0.85 was suggested and same has been implemented here as is done in the ensuing literature. Given the enormous literature on network centralities, we do not elaborate on the mathematical details of PageRank here (see e.g. Newman 2018). For our purpose, we note that the solution of equation (3) is clearly a fixed point of the recursion which can be solved either iteratively starting from some initial guesses, or algebraically at the fixed point itself.

‡ Although we do not use the variable 'total assets' as an instrument since it does not solve the problem of exogenous variation in the present context, we confirm that it is negatively related to vulnerability measures with high statistical significance.

§ In all the analysis below, we have taken the log of market capitalization in 2018 i.e. the end-point of the dataset, as the instrument. But we have checked with log of market capitalization with other years from 2013 to 2017 as well and the results are robust.

¶ Ang *et al.* 2006 found that stocks with high senstivities to innovations in aggregate volatility proxied by changes in the VIX index have low average returns. This motivated us to include the index as an explanatory variable for the vulnerability of stocks.

‖ Baker and Wurgler 2006, 2007 proposed an index of investor sentiment based on the first principal component of five (standardized)

Pastor-Stambaugh liquidity indices.† All the data are in a monthly frequency ranging from January 2013 to December 2018. We estimate the coefficients in the following specification of a cross-section of returns.

$$\begin{aligned} & \textit{Stock returns}_{it} \\ & = \beta_0 + \beta_i Z_t + \epsilon_{it}, \quad i = 1, \ldots, N;\ t = 1, \ldots, T \end{aligned} \tag{5}$$

where Z represents the explanatory variables considered. β_i represents the sensitivity of returns to the variables. In this multivariate setup, we obtain $\beta_{Excess-return-factor}$, $\beta_{SMB-factor}$, $\beta_{HML-factor}$, β_{VIX}, $\beta_{sentiment}$, $\beta_{Aggregate-Liquidity}$, $\beta_{Innovations-in-Liquidity}$ and $\beta_{Traded-liquidity-factor}$ for a cross-section of $N = 282$ firms in the baseline estimation. These computed values are used as instruments for stock PageRank in explaining bond PageRank.

Section 3.1 discusses the results of the instrumental variable regression. Descriptions of all variables are listed in table 1 along with data sources. We present summary statistics of all the variables in table 2 for the baseline specification. Firm names along with ticker symbols, CUSIP ids and exchange codes indicating the stock market they are registered in, have been described in the appendix (table A1).

3. Vulnerability: linkage between the networks of stocks and bonds

In this section, we discuss the baseline model and the results. The main specification we estimate in cross-section is as follows:

$$\begin{aligned} & \log(\textit{bond PageRank})_i \\ & = \beta_0 + \beta_{sr} \log(\textit{stock PageRank})_i + \beta X_i + \epsilon_i, \\ & \quad i = 1, \ldots, N \end{aligned} \tag{6}$$

where log(*bond PageRank*) represents log of bond PageRank, log(*stock PageRank*) represents log of stock PageRank, X represents control variables, including responsiveness of each asset to money market factors, short and long term on-off spread, Cochrane-Piazzesi factor, term spread and default spread. Our main interest is in the coefficient β_{sr} representing the relationship between two vulnerability measures. A positive relationship would imply that high vulnerability in the stock market is related to high vulnerability in the bond market. In the following, we first elaborate on regression results and next, we provide results obtained from instrumental variable regressions.

Table 3. Regression results of log(bond PageRank) on log (stock PageRank) with covariates.

	Dependent variable:		
	log(bond PageRank)		
	(1)	(2)	(3)
log(stock PageRank)	0.150**	0.152**	0.151**
	(0.0579)	(0.0591)	(0.0596)
controls		y	y
Constant	− 4.982***	− 4.952***	− 4.948***
	(0.357)	(0.366)	(0.370)
Observations	282	282	282
F	6.741	3.270	5.360
Adjusted R^2	0.019	0.024	0.020

Notes: Model (1) represents OLS results with no control variables. Model (2) controls for responsiveness of stocks to money market, medium and long term spreads. Model (3) additionally controls for Cochrane-Piazzesi factors, term and default spreads. The relationship between PageRanks across stocks and bonds is stable and incorporating the responsiveness coefficients does not impact the relationship. Errors have been clustered at two-digits SIC codes. Standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

The main results are summarized in table 3. Model (1) regresses $log(bond\ PageRank)$ on $log(stock\ PageRank)$. The positive and significant relationship indicates that if a firm has a higher vulnerability in the stock network, it is more likely to have higher vulnerability in the bond network as well. In particular, given the log-log specification, 1% increase in vulnerability in the stock market for a firm is associated with 0.15 % increase in the vulnerability in the bond market.‡ In the remaining models (models (2) and (3)), we add control variables comprising money market, medium and long term spreads, Cochrane-Piazzesi factors, term and default spreads. The coefficient estimates of β_{sr} in equation (6) are quite robust. None of the responsiveness parameters seems to possess explanatory power for vulnerability (not reported).

3.1. Effect of firms' fundamentals: IV results

As we noted in section 2.5, there can be endogeneity in the relationship between stock and bond market vulnerabilities due to the simultaneous estimation of those measures. Here we instrument stock centrality by firms' fundamentals, and we show that the main results hold. The set of instruments

sentiment proxies where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic indicators. The five proxies are trading volume as measured by NYSE turnover, the dividend premium, the closed-end fund discount, the number and first-day returns on IPOs, and the equity share in new issues. We use the index derived in equation (3) of the paper.

† Pástor and Stambaugh 2003 find that cross-section of expected stock returns is related to the sensitivities of returns to changes in aggregate liquidity. We use three liquidity indices given in the paper, which are levels of aggregated liquidity (figure 1 in the paper) and innovations in aggregated liquidity (non-traded liquidity factor, given by the main series in equation (8) in the paper, and traded liquidity factor (LIQ_V, 10-1 portfolio return) respectively.

‡ Here we note that there are firms who have issued multiple bonds and we have considered the first principal component of the bond returns for our calculations as described in section 2.2. One question might arise as to whether the choice of the principal component is influencing the result or not. To address this concern, we have estimated the same model on two alternate samples; the first estimation is done with average bond returns for firms issuing more than one bond, and the second estimation is done excluding all firms which issued more than one bond and retained only the firms that issued exactly one bond. In both cases, we recover quantitatively similar result in terms of magnitude and significance of the coefficient β_{sr} in equation (6).

we have considered comprises firm size in terms of market capitalization, profitability in terms of earnings per share and dividends per share, responsiveness of firms with respect to the three Fama-French factors, CBOE volatility index (VIX), Baker-Wurgler sentiment index and Pastor-Stambaugh liquidity index. Notably, our usage of stock market capitalization† is motivated by the idea that it would potentially directly impact vulnerabilities of the firms in the stock market, capturing the effect that 'too big to fail' firms tend to be 'too central to fail'.

We have employed the instruments in three sets. The first one contains only market capitalization, the second one contains market capitalization and EPS, DPS, whereas the third set contains all of the instruments. Table 4 summarizes the results. Firm size explains a substantial part of the variability in the vulnerability measure. The main result remains quite robust that stock PageRank is positively related to bond PageRank. Additionally, the first stage IV regression results have been presented in table A2 in the appendix. The coefficient of size on vulnerability is negative and significant at 1%. Other variables are not consistent in their explanatory power. The effect of firm size on vulnerability is along the expected line. Intuitively, a large firm would be less vulnerable compared to a smaller firm, controlling for all other factors. We find empirical support for this argument from first stage regression in table A2 with F-statistic being more than 10 in all cases. Column (1) has market capitalization as the only instrument. Columns (2) and (3) incorporate a larger set of firm-specific variables as instruments, for robustness. The results are consistent across three models. As an additional robustness check, we employed a shrinkage estimator in the form of LASSO regression on the first-stage specification with optimal penalty parameters chosen by multiple types of information criteria. In all cases, the 'market capitalization' variable is retained as an explanatory variable.

4. Robustness of vulnerability spillover: stocks and bonds

In this section, we perform various robustness checks on our baseline result. We find that the result is robust to controlling for market-level factors, the time horizon of the sample, lag selection of construction of the Granger Causal Network, bond maturity horizons and bond types as well as volatility-adjustment to returns. We provide each estimation result along with the baseline result in the same table for ease of comparison.

4.1. Choice of PageRank as the vulnerability measure

Our choice of PageRank of the Granger Causal Network (GCN) is motivated by the previous work by Billio *et al.* (2012) and Yun *et al.* (2019). One question might appear in terms of the suitability of PageRank for capturing vulnerability vis-a-vis other network centrality measures. In order to check behavior of PageRank with respect to other measures, we have computed five other centrality measures (closeness, betweenness, in-degree, out-degree, eigenvector) based on the Granger Causal Networks and reported their correlation coefficients with PageRank in table A9 for stocks and table A10 for bonds. As expected, PageRank is highly correlated with eigenvector centrality as PageRank is a modified version of eignvector centrality Page *et al.* 1999. Notably, it is also highly correlated with in-degree (and negatively correlated with out-degree), which is expected because both measures capture vulnerability.

4.2. Variation in time horizon of estimation

Next, we check how robust is the relationship with respect to varying time-length of the sample. Table A3 presents the results. We have varied the time window from three years to six years (baseline). For the largest sample (2013–18), the sample used for baseline estimation constitutes 282 firms. This number has been arrived at by making sure that the other ancillary data for this set of firms would be available. For the purpose of this analysis, we collect bond and stock price data for the largest set of firms available, which consists of 351 firms. Then we regress log of bond PagRank on log of stock PageRank for four consecutive windows with increasing lengths, starting from 2013–2015 (three years) to 2013–2018 (six years).

We observe that a significant relationship between stock and bond PageRank exists for all the windows except for the three years' window. This is to be expected since the Granger Causality relationship estimation depends on the length of the available data. With monthly data, three years' window may be too small to capture the relationship. As shown in table A3, as we increase the time horizon, the relationship becomes stable and stronger. This is consistent with the idea that in order to construct the GCN credibly, the causality needs to be inferred correctly and hence, it requires a larger time window for proper estimation.

In this context, it is important to point out that we have deliberately kept the period before 2012 out of the present analysis. The first reason is that there is a data mismatch (data for all firms do not exist, especially for the control variables). The second and more important reason is that both the stock and bond markets were turbulent during that period due to the lagged effects of the 2007–2009 financial crisis and the interventions that followed. Therefore our analysis solely focuses on data from the stock and bond markets after 2012 when the markets returned to normalcy.

4.3. Lag order selection

Here we check the robustness of the results with respect to different lag orders in the Granger causality estimation. We construct the GCNs with three different lag orders, namely, 1, 2 and 3. The results reported in table A4 indicate that the relationship persists for lag orders of 2 and 3.

This is related to the fact that stock and bond returns adjust at different frequencies. Given the longer time horizons of maturity, bond returns might be slow-moving, less volatile

† As explained in section 2.5, we excluded the variable 'total assets' as an instrument since that does not solve the problem of endogeneity in the present context, although it is negatively correlated to the vulnerability measure with high statistical significance.

Table 4. IV regression results of log(bond PageRank) on log (stock PageRank).

	Dependent variable:					
	log(bond PageRank)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(stock PageRank)	1.296***	1.052***	0.628***	1.260***	1.037***	0.626***
	(0.328)	(0.231)	(0.157)	(0.334)	(0.233)	(0.153)
controls				y	y	y
Constant	1.730	0.298	– 2.187**	1.590	0.279	– 2.149**
	(1.914)	(1.352)	(0.929)	(1.974)	(1.381)	(0.914)
Observations	282	282	282	282	282	282
F	15.24	20.18	15.58	2.911	3.587	4.377
Hansen J statistic	–	1.153	15.604	–	1.02	11.983
p-value (J statistic)		0.5618	0.1116		0.6005	0.2862

Notes: Models (1) and (4) are IV regressions where log(stock PageRank) is instrumented with market capitalization. Models (2), (5) use market capitalization, EPS and DPS as instruments and models (3) and (6) use market capitalization, EPS, DPS and sensitivities (β variables; see section 2.5) of stock returns with respect to three Fama-French factors, Pastor-Stambaugh liquidity factors, Baker-Wurgler sentiment index and vix as instruments. The same set of controls from table 3 are present. Errors have been clustered at two-digits SIC codes. Standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

and require a longer time of adjustment to reflect underlying information content. On the other hand, stock returns are often prone to quick adjustments that might overshoot and is also subjected to misinformation and herding behavior. The differential speeds of reaction across stocks and bonds are consistent with the finding that in the in case of larger lags, the relationship prevails. It is noteworthy that the coefficients not only have the same sign but also are quite similar in magnitude in case of lags 2 and 3.

4.4. Heterogeneous classes of bonds: variation in maturities and types

In our baseline model, we had considered bonds with a maturity of 10 years. In this section, we consider bonds of different maturities and also bonds other than the ones considered in the baseline model (see table A1 for the CUSIP ids) and we find that the relationship between a firm's vulnerability in stock and bond market persists. In particular, we have considered additional non-convertible bonds such as senior unsecured debenture, senior debenture, junior subordinated debenture, subordinated unsecured debenture, capital security, junior subordinated unsecured preferred security (trust, SPV), subordinated unsecured bank note, unsecured debenture, mortgage pass-through certificate, subordinated unsecured depositary preferred share, subordinated bank note, senior secured pass-through certificate, first and refunding mortgage bond, first mortgage note, subordinated unsecured preferred security (trust, SPV), first lien note, first and refunding mortgage note, junior unsecured or junior subordinated unsecured capital security, subordinated unsecured preferred stock, structured product, subordinated unsecured capital security. These securities have variations in terms of floating or fixed coupons.

In table A5, we have presented the robustness checks with bonds with maturity in medium terms (4–10 years) as well as long term (more than 10 years) and a larger set of bonds including the non-convertibles with 10 years' maturity. We have chosen the largest set of firms for which both bond and stock data are available. The results for different maturities have been reported in the third and fourth columns, which indicates that the relationship is robust. For ease of comparison, the first column provides the baseline model's result. Finally, we consider non-convertibles along with the bonds we considered in the baseline model, with the criteria that the maturity has to be 10 years. The last column in the same table presents the result, which shows the positive relationship holds.

4.5. Residual-based analysis after controlling for aggregate movements

One possibility is that the variation in the vulnerabilities across the stocks can be attributed to market-level factors and how they impact individual asset returns. In the baseline results, we constructed the GCN for stocks from the raw returns. In this exercise, we regress stock returns on the Fama-French factors (market excess return over the risk-free rate, SMB and HML) to extract the residuals that are orthogonal to the factors and use the residuals for construction of the GCN for stocks. We find that the correlation between the vulnerability of stocks and bonds exists even after controlling for common risk factors affecting stock returns, as shown in table A6. The first column describes the results with the baseline scenario (equivalent of column 1 in table 3) and the second column describes the results with residuals.

4.6. Correction due to latent volatility adjustments and robustness for comovement matrix

Finally, we conduct another robustness check in terms of volatility adjustment of the stock return series to rule out the possibility that the relationship is affected by the correlation structure induced by spurious correlation arising due to latent volatility. We use a GARCH(1, 1) specification for each return series

$$r_t = \sigma_t \xi_t \tag{7}$$

where conditional volatility evolves as

$$\sigma_t^2 = \omega + \alpha\xi_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (8)$$

and ξ is an error term. For each stock return series, we normalize it by the corresponding estimated latent volatility. The GCN is created out of the normalized return series. Table A7 presents the baseline and the GARCH-adjusted results. We observe that the result persists albeit with a slightly smaller magnitude of the coefficient.

For an additional comparison, we have also analyzed if the results hold with respect to comovement matrices instead of the lagged comovement analysis (we note that Granger causal network represents lagged movements). In order to do that, we first construct Pearson correlation matrices and extract the corresponding PageRank vectors. These vectors do not have the same interpretation of vulnerabilities as we have followed so far. Instead, these represent the contribution of the assets to the dominant eigenvector (if we strictly consider the interpretation of eigenvector centrality; PageRank is a function of eigenvector centrality). We see in table A7 that even with comovement matrices, a positive relationship between the PageRank vectors exists. However, centrality-measures from comovement matrices do not have an immediate interpretation in terms of vulnerabilities. A recent literature has considered this kind of graph-theoretic approach to studying equity market interconnectedness (Sinha *et al.* 2010, Di Cerbo and Taylor 2021). The methodology we follow goes beyond capturing only the contemporaneous movements in asset returns and, provides a more comprehensive view of the directional dynamic relationships between assets. Consequently, it also brings forth a concise treatment of centrality-based concept of vulnerability which is absent in comovement-based measures.

4.7. Comparison with other measures of systemic risk: CoVaR and MES

In order to probe further into the nature of vulnerability in the stock GCN, we compare the measure we have analyzed so far, with measures of systemic risk that exist in the literature. In particular, we have analyzed how closely the stock PageRank is related to conditional value at risk (CoVaR; Adrian and Brunnermeier 2016) and marginal expected shortfall (MES; Acharya *et al.* 2017). Although there are some other measures in the literature, these two measures are probably the most well known measures of systemic risk at the firm-level apart from the one we have considered in this paper. We are not aware of similar systemic risk measurement in the context of bond markets. Therefore, we exclude the bond market from this comparative analysis.

We evaluate the CoVaR as well as a marginal expected shortfall for the stocks and perform univariate regression of log of stock PageRank on both CoVaR and MES. In table A8, we have reported the results. The PageRank measure does not show a relationship with marginal expected shortfall. But it is correlated to CoVaR at different percentiles. Surprisingly, the sign of the relationship changes from low to high percentiles. This lack of a robust relationship between different measures of systemic risk and vulnerability has been noted in the literature (Yun *et al.* 2019).

4.8. Two crisis periods

Given that the main result is based on the period 2013–2018 which did not see any major financial crisis, one can ask what would have been the relationship during the crisis periods. There are two notable crisis periods prior and post the period under consideration. The financial crisis was from 2007 to 2009 and the Covid-19 driven pandemic was from 2020 to 2021 (currently ongoing). Since both of these two crises have economic impacts, here we estimate the relationship during the crisis periods to complement the estimate during the calm period of 2013–2018.†

We first consider the global financial crisis (GFC). We take two windows (2007–2010 and 2009–2012) to provide a comparison between during-crisis and post-crisis periods. Consistent with the sample selection above, here also firms are selected such that the bonds issued are traded at least once a month during the periods of analysis. A sample of 160 firms remain after the intersection of sample sets for periods 2007–2010 and 2009–2012. Due to data constraints, we were unable to include the period preceding the global financial crisis in our analysis.‡ Following the main specification given in equation (6), we regress the log(bond PageRank) on log(stock PageRank) and show the results in table A12. Refer to the first column for the crisis period and the second column for the corresponding non-crisis period, for the same set of firms. To ensure parity of results with the baseline model, we consider bonds with 10-year maturity for both the periods. For the non-crisis period from 2009 to 2012, the coefficient of log(stock PageRank) is 0.166 (similar in magnitude to our baseline result in table 3) and is significant. For the crisis period, the vulnerability in the stock market seems to be uncorrelated to the vulnerability in the bond market, whereas the non-crisis period is marked by a positive relationship.

Next, we implement the same estimation during the COVID-19 crisis with two windows (2015–2018 and 2017–2020). In this case, the sample consists of 388 firms (constructed in the same way as other samples). The results are shown in table A13 and the coefficients are insignificant. We note that given that the Covid-19 pandemic has been in existence for one year (during 2020; our data ends by the beginning of 2021) and still continuing, it is unlikely that its effects can be estimated precisely based on the current dataset.

However, while such exercises give us a more complete picture of the relationship, there are many caveats to make inference based on these results. In particular, it is tempting to infer from table A12 that crisis periods are marked by non-existent relationships and the relationship hold only during relatively calm periods. However, we note that since we estimate the Granger Causal Network from time-series data, a longer time horizon is required to correctly estimate the network (as discussed earlier in section 4.2). Unfortunately, a longer window (say for six years as in the baseline model) will cover both the crisis periods and non-crisis periods. Thus a clean separation between crisis and non-crisis periods is not feasible given the nature of the data. One can argue that

† We thank the reviewers for suggesting these two estimations.
‡ TRACE database was fully implemented in 2005 (see Bessembinder *et al.* 2008)

identification based on a sharp split between crisis and non-crisis periods would be possible using time-series of higher frequency data. However, that would come with flat regions in bond prices, since bonds are not traded as frequently as stocks. Additionally, crises are heterogeneous in duration, cause and impact. The variety of institutional measures and policy responses add to the complexity, which is difficult to control for in the regression models. To summarize, in future, more data covering crisis and non-crisis periods may allow us to infer on the time-varying relationship between stock and bond market vulnerabilities, and possibly go beyond the scope of the current work.

5. Non-parametric analysis: *k*-means clustering

In this section, we conduct non-parametric analysis to establish the link between the stock market and bond market vulnerabilities in a more coarse-grained way. Towards that objective, we utilize *k*-means clustering, which is a popular clustering methodology, mostly used in the machine learning literature. Cai *et al.* (2016) surveys clustering analysis used in financial analysis lists several methods used to understand the structure underlying the financial data. The authors list the following clustering methods, which are generally used in exploratory analysis of data, broadly as, namely, partitioning methods, density-based methods and data-stream clustering methods. We use the *k*-means clustering method (James and Witten 2013) which can be classified under partitioning, to summarize the structural information in the GCNs constructed for stocks and bonds.

This method minimizes within-cluster variance with an exogenously specified number of clusters, where each cluster represents separate groups of nodes. We apply this algorithm to extract the underlying structure in the GCNs by uncovering natural groups in terms of the vulnerabilities of the firms in the stock and bond market networks. Our objectives are twofold. First, we want to compare the relative positions of the firms in the clusters to examine the degree of overlaps between clusters in the stock and the bond markets. A large overlap between the clusters in the stock market and the bond market would indicate a high degree of correlation (in a more coarse-grained way). The second objective is to examine the relationship between the centers of the clusters and the corresponding average sizes (in terms of market capitalization). A negative relationship would indicate that clusters with high average PageRank (i.e. high vulnerability) comprise firms with smaller average size. Both of these features would corroborate and complement the earlier findings in a non-parametric way.

Figure 2 exhibit the clusters generated with the algorithm run for $k = 2, 3, 4$ and 5 in a clockwise fashion. Each point on the scatterplots indicates a firm with its bond PageRank plotted on the *y*-axis in logarithm and the stock PageRank plotted on the *x*-axis in logarithm. For each plot, we have also plotted the centroids of the clusters, where the *y*-coordinate of each centroid represents the average log bond PageRank of firms belonging to that cluster and the *x*-coordinate represents the average log stock PageRank of firms belonging to that cluster. For visual reference, we have also shown the best fit line through these centroids. As the figure shows, there is a positive relationship between the PageRanks across the clusters. This finding is consistent with the observation in a regression framework shown in table 3. Even a coarse-grained clustering setup indicates the existence of the relationship between the vulnerabilities of a firm in the stock and bond markets.

For both the stock and bond market, we present the number and identity (denoted by #) of the clusters, the number of firms in the clusters ($N_{\#}$), the average PageRank ($E(PR)$) and average (log of) market capitalization ($E(mcap)$) in table A11. We observe that the cluster center with a lower stock PageRank corresponds to a relatively higher average market capitalization. For k =2, the second cluster with center at -5.99 has an average log(market capitalization) of 17.52. This indicates that a cluster with a lower value of PageRank as center, is more likely to contain a less vulnerable firm, and is more likely to have a higher average market capitalization.

Figure A1 exhibit the clusters generated with each point on the scatterplots indicating a firm with its stock PageRank plotted on the *y*-axis in logarithm and the market capitalization plotted on the *x*-axis in log scale and figure. A2 plots total assets on the *x*-axis in log scale. Following the same algorithm as in figure 2, we have plotted the centroids of the clusters, where the *y*-coordinate of each centroid represents the average log stock PageRank of firms belonging to that cluster in both figures A1 and A2 and the *x*-coordinate represents the cluster-wise average of log market capitalization in figure A1 and the *x*-coordinate represents the cluster-wise average of log total assets of firms in figure A2. The best fit line in figure A1 through these centroids visually indicates a negative relationship between the stock PageRank and market capitalization across the clusters. This finding is consistent with the observation in the first stage of the IV regression framework shown in table A2. In addition, Figure A2 also exhibits a similar negative relationship between total asset and stock PageRank across clusters. This supports our claim in section 3.1 that large firms are more likely to be less vulnerable in the network.

From these observations, we find support for the findings reported in section 2.5 on the linkage between the stock and bond PageRanks through market capitalization.

6. Summary and conclusion

Identification and management of vulnerable firms have received enormous attention in recent times, owing to the vulnerability of financial systems to crisis events. The existing measurements evaluate ‘vulnerabilities’ of the firms or their contributions to systemic risk, within a given asset market. However, firms are generally active in multiple asset markets leading to a question of what is the nature of the relationship between vulnerabilities of the same set of firms active in different markets. There is no empirical answer to this question to the best of our knowledge although the implications have great importance for policy making. If the vulnerabilities of firms are highly correlated across markets, then targeted intervention in one market would potentially have positive

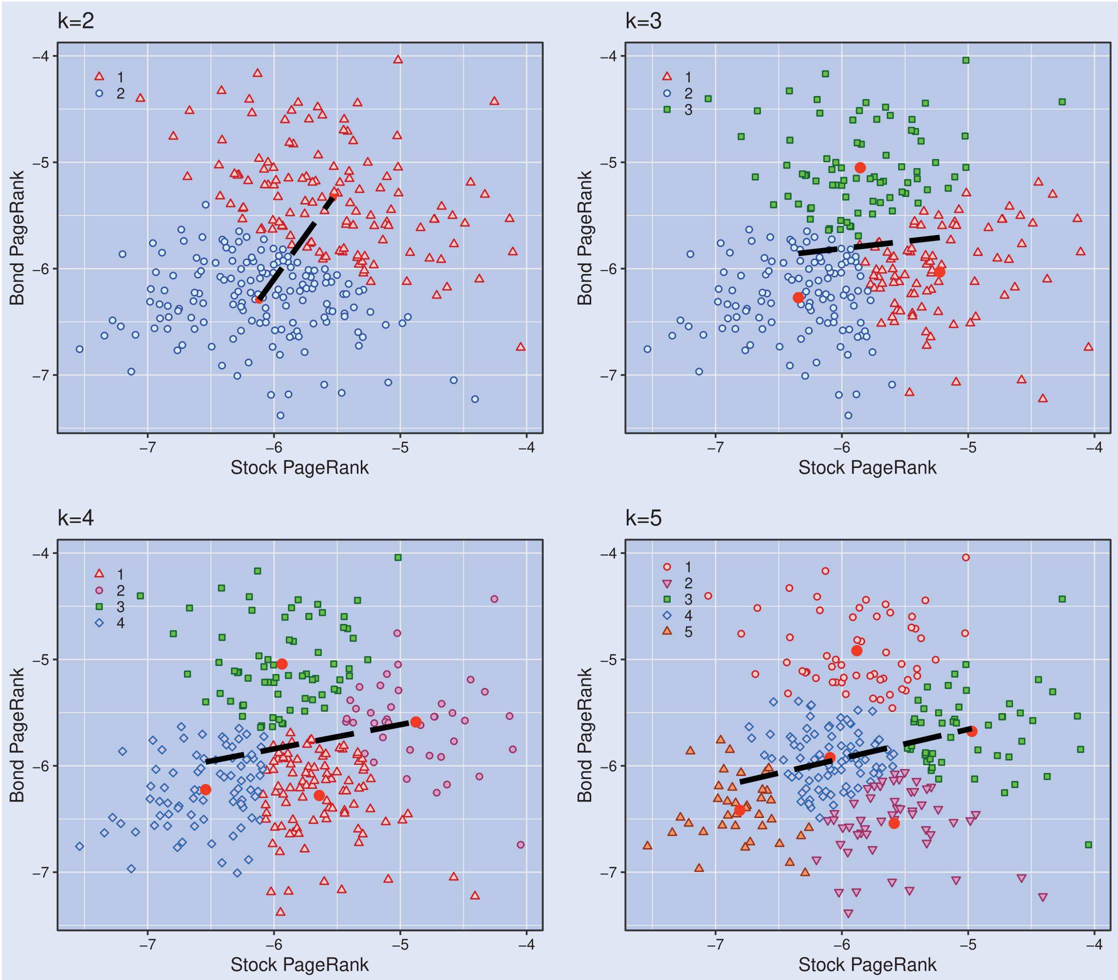

Figure 2. Clustering (k-means) of firms with respect to their bond and stock PageRanks (number of clusters is specified at the top of each panel by k; each cluster is denoted by different color-shape combinations of the points on the scatter plot). The y-axis plots log of bond PageRank and x-axis plots log of stock PageRank of firms. A linear fit across the cluster centers (red filled circles) is shown to capture the positive relationship (black dashed line) between bond and stock PageRanks indicating that vulnerabilities of firms in the bond market are positively related to vulnerabilities in the stock market.

externalities in other markets. However, if the correlation is low, then targeted interventions would not have such positive externalities.

In this paper, we consider firms in the US that are active both in the stock and the bond markets. Our main result is that a firm with a higher vulnerability in the stock market tends to exhibit higher vulnerability in the bond market as well. However, while the relationship is positive and statistically significant, the magnitude is quite low. Our empirical analysis shows that a unit percentage increase in vulnerability for a given firm in the stock market leads to only 0.15 % increase in vulnerability in the bond market. We exploit stock market capitalization and an array of firm-level fundamentals to instrument for vulnerability in the stock market and the results are consistent. Additionally, we show that ‘too-big-to fail’ firms also tend to be ‘too-central-to fail’. Our results are robust with respect to choice of the asset classes, maturity horizons, model specification, time length of the data as well as controlling for all major market-level factors. Finally, we present results based on non-parametric clustering analysis, which corroborates and complements the above findings.

Our findings would appeal to the literature on the management of systemic risk in a multi-asset world with complex interdependence of firms. Our results indicate that targeted intervention in one market will generate minimal positive spillovers in the complementary markets, resulting in a need for separate intervention across asset markets to mitigate risk. Our baseline analysis considers the post-financial crisis (2007-09) and pre-Covid-19 crisis (the global pandemic started around February 2020) periods. When we analyze the financial crisis period and the Covid-19 crisis periods, we see weaker results indicating that possibly the relationship we found in the baseline analysis is time-varying and may change during crisis periods. Future work with more comprehensive datasets may shed more light on the nature and scope of the linkages. Finally, there is an emerging literature with a complementary theme on multiplex financial networks where the multiplexity appears through the statistical properties (see e.g. Musmeci *et al.* 2017) as opposed to the analysis of multiplexity through the market structure as in this paper. Fusing these two different but complementary ways of quantifying risk may lead to more robust measures of vulnerabilities in financial networks.

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Appendices

In this section, we provide the list of all stocks considered along with ticker symbols, name and the list of all bonds issued by those firms. After providing the identifying details, we provide the regression tables along with result from the clustering exercise.

Appendix 1. Identities of the stocks and bonds

In this section, the identifiers of the firms with along their stocks and bonds issued by them are listed. These firms are listed in NYSE (exchange code = 1) or NASDAQ (exchange code = 3) and the returns for the list of these firms is considered for a period of six years from 2013 to 2018.

Appendix 2. Additional regression tables

Table A1. List of firms and their stocks and bonds.

Serial	Name of the firm	Ticker	CUSIP						Exchange
1	Agilent Technologies Inc	A	00846UAG6	00846UAH4					1
2	Advance Auto Parts Inc	AAP	00751YAA4	00751YAB2					1
3	A B B Ltd	ABB	00037BAB8						1
4	Amerisourcebergen Corp	ABC	03073EAJ4						1
5	Adobe Systems Inc	ADBE	00724FAB7						3
6	Archer Daniels Midland Co	ADM	039483BB7						1
7	American Electric Power Co Inc	AEP	025537AG6	744533BK5					1
8	Aercap Holdings N V	AER	459745GF6	459745GN9					1
9	Aflac Inc	AFL	001055AJ1						1
10	American International Group Inc	AIG	026874BW6	026874CU9					1
11	Allstate Corp	ALL	020002AX9						1
12	Applied Materials Inc	AMAT	038222AF2						3
13	A M C Networks Inc	AMCX	00164VAC7						3
14	Amgen Inc	AMGN	031162AZ3	031162BB5	031162BD1	031162BG4	031162BM1	031162BN9	3
15	Amkor Technology Inc	AMKR	031652BG4						3
16	Ameriprise Financial Inc	AMP	03076CAE6						1
17	American Tower Corp New	AMT	029912BC5	029912BE1	03027XAA8	03027XAB6			1
18	T D Ameritrade Holding Corp	AMTD	87236YAA6						1
19	Amazon Com Inc	AMZN	023135AJ5						3
20	Apache Corp	APA	037411AZ8						1
21	Anadarko Petroleum Corp	APC	032511BC0	032511BF3					1
22	Air Products & Chemicals Inc	APD	958254AA2	958254AB0					1
23	Amphenol Corp New	APH	032095AB7						1
24	Alexandria Real Est Equities Inc	ARE	015271AC3						1
25	Allegheny Technologies	ATI	01741RAE2						1
26	Atmos Energy Corp	ATO	049560AJ4						1
27	Anglogold Ashanti Ltd	AU	009158AP1	009158AR7	009158AT3				1
28	Avalonbay Communities Inc	AVB	05348EAQ2						1
29	Avnet Inc	AVT	03512TAA9	03512TAC5					1
30	American Express Co	AXP	025816BB4						1
31	Autozone Inc	AZO	053807AQ6	053807AR4					1
32	Boeing Co	BA	097014AL8	097023AW5					1
33	Bank Of America Corp	BAC	06048WBC3	06048WBD1	06048WDW7	06048WFK1	06050WBN4	06050WBP9	1
	Bank Of America Corp	BAC	06050WDD4	06050WDK8	06050WDP7	06050WDR3	06050WDV4	06050WDZ5	
	Bank Of America Corp	BAC	06050WED3	06050WEH4	06051GDZ9	06051GEC9	06051GEH8	06051GEM7	
	Bank Of America Corp	BAC	06051GEU9						
34	Baxter International Inc	BAX	071813BF5						1
35	Barclays Plc	BCS	06739FFS5	06739GAR0	06739GBP3	06740L8C2			1

(*Continued*).

Table A1. Continued.

Serial	Name of the firm	Ticker	CUSIP						Exchange
36	Becton Dickinson & Co	BDX	075887AW9	075887BA6					1
37	Franklin Resources Inc	BEN	354613AJ0						1
38	Briggs & Stratton Corp	BGG	109043AG4						1
39	Bio Rad Laboratories Inc	BIO	090572AP3						1
40	Bank Of New York Mellon Corp	BK	06406HBM0	06406HBU2	06406HBY4				1
41	Blackrock Inc	BLK	09247XAE1	09247XAH4	09247XAJ0				1
42	Ball Corp	BLL	058498AR7						1
43	Bristol Myers Squibb Co	BMY	110122AT5						1
44	B P Plc	BP	05565QBJ6	05565QBP2	05565QBR8	05565QBU1	05565QBZ0	05565QCB2	1
45	Buckeye Partners L P	BPL	118230AH4	118230AJ0					1
46	British American Tobacco Plc	BTI	544152AB7	761713AX4					1
47	Anheuser Busch Inbev Sa Nv	BUD	03523TBB3	03523TBP2	035242AA4				1
48	Borgwarner Inc	BWA	099724AG1						1
49	Boston Properties Inc	BXP	10112RAQ7	10112RAR5					1
50	Citigroup Inc	C	172967EV9	172967FF3					1
51	Cardinal Health Inc	CAH	14149YAT5	14149YAV0					1
52	Caterpillar Inc	CAT	149123BV2	149123BX8	14912L4E8	14912L5F4			1
53	Celanese Corp Del	CE	15089QAC8	15089QAD6					1
54	C N O O C Ltd	CEO	65334HAK8						1
55	C F Industries Holdings Inc	CF	12527GAB9						1
56	Church & Dwight Inc	CHD	171340AH5						1
57	Choice Hotels International Inc	CHH	169905AD8	169905AE6					1
58	Chesapeake Energy Corp	CHK	165167CC9	165167CF2	165167CG0				1
59	Charter Communications Inc	CHTR	1248EPAY9	88732JAS7	88732JBA5				3
60	C I T Group Inc New	CIT	125581GQ5						1
61	Colgate Palmolive Co	CL	19416QDR8	19416QDY3	19416QDZ0				1
62	Cleveland Cliffs Inc	CLF	18683KAD3						1
63	Mack Cali Realty Corp	CLI	55448QAQ9						1
64	Continental Resources Inc	CLR	212015AH4						1
65	Clorox Co	CLX	189054AS8	189054AT6					1
66	C M E Group Inc	CME	12572QAE5						3
67	Centerpoint Energy Inc	CNP	15189WAG5						1
68	Capital One Financial Corp	COF	14040HAY1						1
69	Coca Cola Bottling Co Cons	COKE	191241AD0						3
70	Conocophillips	COP	20826FAA4	718546AC8					1
71	Campbell Soup Co	CPB	134429AT6	134429AW9	134429AY5				1
72	Camden Property Trust	CPT	133131AT9						1
73	Carpenter Technology Corp	CRS	144285AJ2						1
74	Credit Suisse Group	CS	22546QAC1	22546QAD9	22546QAF4				1
75	Cisco Systems Inc	CSCO	17275RAE2						3

(*Continued*).

Table A1. Continued.

Serial	Name of the firm	Ticker	CUSIP						Exchange
76	C S X Corp	CSX	126408GT4	126408GV9					3
77	Centurylink Inc	CTL	156700AN6	156700AR7	156700AS5				1
78	C V S Health Corp	CVS	126650BW9	126650BZ2					1
79	Chevron Corp New	CVX	166751AJ6	166764AB6					1
80	Dominion Resources Inc Va	D	25746UBH1	25746UBL2	25746UBP3	927804FH2	927804FK5		1
81	Deere & Co	DE	244199BC8	244199BE4	24422ERE1	24422ERH4	24422ERM3		1
82	Diageo Plc	DEO	25243YAP4	25245BAB3					1
83	Discover Financial Services	DFS	254709AE8	254709AG3					1
84	Quest Diagnostics Inc	DGX	74834LAS9						1
85	D R Horton Inc	DHI	23331ABE8	23331ABG3					1
86	Disney Walt Co	DIS	25468PCK0	25468PCL8	25468PCN4	25468PCT1	25468PCW4		1
87	Dish Network Corporation	DISH	25470XAB1	25470XAE5	25470XAJ4				3
88	Denbury Resources Inc	DNR	247916AC3	24823UAH1					1
89	Dover Corp	DOV	260003AJ7						1
90	Duke Realty Corp	DRE	26441YAV9	26441YAW7					1
91	D T E Energy Co	DTE	250847EJ5						1
92	Duke Energy Corp New	DUK	26441CAD7	26441CAF2	26441CAJ4	743263AN5	743263AQ8	743263AR6	1
	Duke Energy Corp New	DUK	743263AS4						
93	Davita Healthcare Partners Inc	DVA	23918KAP3						1
94	Devon Energy Corp New	DVN	25179MAH6	25179MAK9	25179MAP8				1
95	Ebay Inc	EBAY	278642AC7	278642AE3					3
96	Ecolab Inc	ECL	278865AL4						1
97	Equifax Inc	EFX	294429AJ4						1
98	Lauder Estee Cos Inc	EL	29736RAE0						1
99	Eastman Chemical Co	EMN	277432AN0						1
100	Emerson Electric Co	EMR	291011AY0	291011BA1					1
101	Eog Resources Inc	EOG	26875PAD3	26875PAE1					1
102	E P R Properties	EPR	29380TAT2						1
103	Equity Residential	EQR	26884AAY9	26884AAZ6					1
104	E Q T Corp	EQT	26884LAA7	26884LAB5					1
105	Ericsson	ERIC	294829AA4						3
106	Embraer S A	ERJ	29082AAA5						1
107	Eaton Corp Plc	ETN	278058DH2						1
108	Entergy Corp New	ETR	29364GAF0	29365TAA2					1
109	Exelon Corp	EXC	059165EE6	210371AL4	30161MAF0	30161MAH6			1
110	Expedia Group Inc	EXPE	30212PAH8						3
111	Ford Motor Co Del	F	345397VR1	345397VU4	345397WF6				1
112	Freeport Mcmoran Inc	FCX	35671DAU9						1
113	Fiserv Inc	FISV	337738AL2	337738AM0					3
114	Fifth Third Bancorp	FITB	316773CL2						3

(*Continued*).

Table A1. Continued.

Serial	Name of the firm	Ticker	CUSIP						Exchange
115	Flowserve Corp	FLS	34354PAC9						1
116	Fidelity National Finl Inc New	FNF	31620RAF2						1
117	F M C Technologies Inc	FTI	30249UAB7						1
118	Frontier Communications Corp	FTR	35906AAH1						3
119	General Dynamics Corp	GD	369550AR9	369550AU2					1
120	General Electric Co	GE	369604BD4	369622SM8	36962G4D3	36962G4J0	36962G4R2	36962G4Y7	1
	General Electric Co	GE	36962G5J9	36962G6F6	36962G6S8	36966R7H3			
121	Greif Inc	GEF	397624AG2						1
122	Gilead Sciences Inc	GILD	375558AQ6	375558AU7					3
123	Corning Inc	GLW	219350AU9						1
124	Genworth Financial Inc	GNW	37247DAM8	37247DAP1					1
125	Goldman Sachs Group Inc	GS	38141E6N4	38141EA25	38141EA58	38141EA66	38141EP45	38141GGQ1	1
	Goldman Sachs Group Inc	GS	38141GGS7	38141GRD8					
126	Glaxosmithkline Plc	GSK	377373AD7						1
127	Goodyear Tire & Rubber Co	GT	382550BA8						3
128	Hyatt Hotels Corp	H	448579AD4						1
129	Halliburton Company	HAL	406216AZ4						1
130	Hillenbrand Inc	HI	431571AA6						1
131	Hartford Financial Svcs Grp Inc	HIG	416515AZ7	416518AB4					1
132	Honeywell International Inc	HON	438516BA3						1
133	Hewlett Packard Co	HPQ	428236BF9	428236BM4	428236BQ5	428236BV4	428236BX0		1
134	Host Hotels & Resorts Inc	HST	44107TAS5						1
135	Hershey Co	HSY	427866AR9						1
136	Hertz Global Holdings Inc	HTZ	428040CG2						1
137	Humana Inc	HUM	444859BA9						1
138	International Business Machs Cor	IBM	459200HA2	459200HG9					1
139	Intel Corp	INTC	458140AJ9	458140AM2					3
140	Interpublic Group Cos Inc	IPG	460690BH2						1
141	Illinois Tool Works Inc	ITW	452308AJ8						1
142	Invesco Ltd	IVZ	46132FAA8						1
143	Jabil Circuit Inc	JBL	466313AF0	466313AG8					1
144	Johnson Controls Intl Plc	JCI	478366AU1	478366BA4					1
145	Johnson & Johnson	JNJ	478160AW4	478160AZ7					1
146	Juniper Networks Inc	JNPR	48203RAF1						1
147	Jpmorgan Chase & Co	JPM	46625HHL7	46625HHQ6	46625HHS2	46625HHU7	46625HHZ6	46625HJC5	1
	Jpmorgan Chase & Co	JPM	46625HJD3	46625HJE1	46625HJH4	48125XEH5			
148	Kellogg Co	K	487836BC1	487836BD9	487836BJ6				1
149	K B Home	KBH	48666KAR0						1
150	Keycorp New	KEY	49326EED1						1

(*Continued*).

Table A1. Continued.

Serial	Name of the firm	Ticker	CUSIP						Exchange
151	K K R & Co Lp	KKR	97063PAB0	970648AE1					1
152	Kimberly Clark Corp	KMB	494368BE2	494368BH5					1
153	Kinder Morgan Inc	KMI	494550BE5	494550BL9					1
154	Coca Cola Co	KO	191216AR1	191216AV2					1
155	Loews Corp	L	096630AB4						1
156	Laboratory Corp America Hldgs	LH	50540RAJ1	50540RAL6					1
157	Lockheed Martin Corp	LMT	539830AT6	539830AY5					1
158	Lincoln National Corp	LNC	534187BB4	534187BC2					1
159	Lloyds Banking Group Plc	LYG	539473AH1	53947QAA5					1
160	Mid America Apt Communities Inc	MAA	737415AL3						1
161	Marriott International Inc New	MAR	571903AK9						1
162	Masco Corp	MAS	574599BG0	574599BH8					1
163	Mcdonalds Corp	MCD	58013MEG5	58013MEJ9	58013MEL4				1
164	Moodys Corp	MCO	615369AA3	615369AB1					1
165	M D C Holdings Inc	MDC	552676AP3						1
166	Methanex Corp	MEOH	59151KAG3						3
167	Metlife Inc	MET	59156RBF4						1
168	Mohawk Industries Inc	MHK	608190AJ3						1
169	Markel Corp	MKL	570535AH7	570535AJ3	570535AK0				1
170	Marsh & Mclennan Cos Inc	MMC	571748AR3						1
171	3M Co	MMM	88579YAF8						1
172	Magellan Midstream Ptnrs L P	MMP	559080AE6						1
173	Altria Group Inc	MO	02209SAJ2	02209SAL7	02209SAN3				1
174	Mosaic Company New	MOS	61945CAA1						1
175	Merck & Co Inc New	MRK	589331AN7	589331AT4					1
176	Marathon Oil Corp	MRO	565849AK2	56585AAD4					1
177	Morgan Stanley Dean Witter & Co	MS	6174467P8	61745E5R8	61745E7K1	61745EE72	61745EG47	61747WAF6	1
	Morgan Stanley Dean Witter & Co	MS	61747WAL3	61747YCG8	61747YCJ2	61747YCM5	6174824M3	61760LAB1	
178	Microsoft Corp	MSFT	594918AC8	594918AH7	594918AL8	594918AQ7			3
179	Motorola Solutions Inc	MSI	620076BB4						1
180	Arcelormittal S A Luxembourg	MT	03938LAQ7	03938LAU8	03938LAX2				1
181	Meritage Homes Corp	MTH	59001AAN2						1
182	Murphy Oil Corp	MUR	626717AD4	626717AF9					1
183	Noble Energy Inc	NBL	655044AF2						1
184	Nasdaq Inc	NDAQ	631103AD0						3
185	Noble Corp Plc	NE	65504LAC1	65504LAJ6					1
186	Newmont Mining Corp	NEM	651639AL0	651639AN6					1
187	National Retail Properties Inc	NNN	637417AE6						1
188	Northrop Grumman Corp	NOC	666807BA9						1
189	Nokia Corp	NOK	654902AB1						1
190	National Oilwell Varco Inc	NOV	637071AJ0						1
191	Nustar Energy L P	NS	67059TAB1	67059TAC9					1

(*Continued*).

Table A1. Continued.

Serial	Name of the firm	Ticker	CUSIP					Exchange
192	Norfolk Southern Corp	NSC	655844BC1	655844BG2	655844BJ6			1
193	Northern Trust Corp	NTRS	655844BC1	655844BG2	655844BJ6			3
194	N V R Inc	NVR	62944TAE5					1
195	Newell Brands Inc	NWL	651229AK2	651229AM8				1
196	Realty Income Corp	O	756109AN4					1
197	Oasis Petroleum Inc	OAS	674215AD0					1
198	Owens Corning New	OC	690742AD3					1
199	Oneok Inc New	OKE	682680AQ6	68268NAE3	68268NAJ2			1
200	Olin Corp	OLN	680665AH9					1
201	Omnicom Group Inc	OMC	681919AY2	681919AZ9	682134AC5			1
202	O Reilly Automotive Inc New	ORLY	67103HAC1					3
203	Plains All Amern Pipeline L P	PAA	72650RAY8	72650RAZ5				1
204	Peoples United Financial Inc	PBCT	712704AA3					3
205	Petroleo Brasileiro Sa Petrobras	PBR	71645WAR2					1
206	P G & E Corp	PCG	694308GW1	694308HB6				1
207	Public Service Enterprise Gp Inc	PEG	69362BAY8					1
208	Pepsico Inc	PEP	713448BN7	713448BR8	713448BW7	713448BY3		1
209	Principal Financial Group Inc	PFG	74251VAE2					1
210	Procter & Gamble Co	PG	742718DY2					1
211	Progressive Corp Oh	PGR	743315AN3					1
212	Packaging Corp America	PKG	695156AP4					1
213	Perkinelmer Inc	PKI	714046AE9					1
214	Philip Morris International Inc	PM	718172AH2	718172AK5	718172AL3	718172AT6		1
215	P N C Financial Services Grp Inc	PNC	693476BF9	693476BJ1	693476BL6	693476BN2	69349LAG3	1
216	P P L Corp	PPL	69352JAN7	69352PAD5	69352PAE3			1
217	Prudential Financial Inc	PRU	74432QBG9	74432QBM6	74432QBP9	74432QBT1		1
218	Pioneer Natural Resources Co	PXD	723787AK3					1
219	Q E P Resources Inc	QEP	74733VAB6					1
220	Royal Caribbean Cruises Ltd	RCL	780153AU6					1
221	Reinsurance Group Of America Inc	RGA	759351AG4					1
222	Transocean Ltd	RIG	893830AY5	893830BB4	893830BC2			1
223	Renaissancere Holdings Ltd	RNR	759891AA2					1
224	Roper Industries Inc	ROP	776696AE6					1
225	Range Resources Corp	RRC	75281AAM1	75281AAN9				1
226	Donnelley R R & Sons Co	RRD	257867AW1					1
227	Republic Services Inc	RSG	760759AH3	760759AP5				1
228	Raytheon Co	RTN	755111BT7	755111BX8				1
229	Rayonier Inc New	RYN	754907AA1					1
230	Banco Santander S A	SAN	05967FAB2					1
231	Schwab Charles Corp New	SCHW	808513AD7					1
232	S V B Financial Group	SIVB	78486QAC5					3
233	Southern Co	SO	010392FC7	373334JP7	373334JX0			1
234	Simon Property Group Inc New	SPG	828807CG0	828807CK1				1
235	Sempra Energy	SRE	816851AT6					1
236	Sasol Ltd	SSL	803865AA2					1
237	State Street Corp	STT	857477AG8					1
238	Stanley Black & Decker Inc	SWK	854502AC5	854502AD3				1
239	Southwestern Energy Co	SWN	845467AH2					1

(*Continued*).

Table A1. Continued.

Serial	Name of the firm	Ticker	CUSIP					Exchange
240	Stryker Corp	SYK	863667AB7					1
241	Sysco Corp	SYY	871829AQ0					1
242	A T & T Inc	T	00206RAR3	00206RAX0	00206RAZ5	00206RBD3	00206RBN1	1
243	Molson Coors Brewing Co	TAP	60871RAC4					1
244	Telefonica S A	TEF	87938WAH6	87938WAM5	87938WAP8	P28768AA0	P9047EAA6	1
245	T E Connectivity Ltd	TEL	902133AM9					1
246	Teva Pharmaceutical Inds Ltd	TEVA	88165FAF9	88165FAG7	88166JAA1			1
247	Teekay Corp	TK	87900YAA1					1
248	Thermo Fisher Scientific Inc	TMO	883556AX0	883556AZ5				1
249	Toll Brothers Inc	TOL	88947EAJ9	88947EAK6				1
250	Total S A	TOT	89152UAD4	89152UAF9	89153UAF8	89153VAB5		1
251	Thomson Reuters Corp	TRI	884903BK0					1
252	Travelers Companies Inc	TRV	89417EAF6	89417EAG4				1
253	Tyson Foods Inc	TSN	902494AT0					1
254	Textron Inc	TXT	883203BQ3					1
255	U B S Group A G	UBS	90261AAB8	90261XGD8				1
256	Unitedhealth Group Inc	UNH	91324PBM3	91324PBP6	91324PBT8	91324PBV3		1
257	Unum Group	UNM	91529YAH9					1
258	Unit Corp	UNT	909218AB5					1
259	United Parcel Service Inc	UPS	911312AK2	911312AQ9				1
260	U S Bancorp Del	USB	91159HHA1	91159HHC7	91159JAA4			1
261	United Technologies Corp	UTX	913017BR9	913017BV0				1
262	Vale S A	VALE	91911TAM5					1
263	Valero Energy Corp New	VLO	91913YAR1					1
264	Verisk Analytics Inc	VRSK	92345YAA4	92345YAC0				3
265	Ventas Inc	VTR	92276MAX3	92276MAZ8				1
266	Westpac Banking Corp	WBK	961214BK8					1
267	Wisconsin Energy Corp	WEC	976656CD8					1
268	Wells Fargo & Co New	WFC	94974BEV8	94974BFC9	94986RCE9			1
269	Whirlpool Corp	WHR	96332HCD9	96332HCE7				1
270	Williams Cos	WMB	96950FAD6	96950FAG9	96950FAH7	96950FAJ3		1
271	W P X Energy Inc	WPX	98212BAD5					1
272	Berkley W R Corp	WRB	084423AQ5	084423AS1				1
273	Washington Real Estate Invs Tr	WRE	939653AM3					1
274	Weingarten Realty Investors	WRI	948741AH6					1
275	White Mountains Ins Group Inc	WTM	68245JAB6					1
276	Western Union Co	WU	959802AL3					1
277	Weyerhaeuser Co	WY	962166BV5					1
278	United States Steel Corp New	X	912909AF5					1
279	Exxon Mobil Corp	XOM	98385XAT3					1
280	Xerox Corp	XRX	984121CA9	984121CD3				1
281	Alleghany Corp De	Y	017175AB6	017175AC4				1
282	Yum Brands Inc	YUM	988498AF8	988498AG6	988498AH4			1

Table A2. Regression Results: First stage results of the IV regression. Size is negatively related to vulnerability.

	Dependent variable:		
	log(stock PageRank)		
	(1)	(2)	(3)
log(market capitalization) (2018)	– 0.109***	– 0.0897***	– 0.0873***
	(0.0215)	(0.0313)	(0.0282)
Earnings per share (2018)		0.00352	0.00365
		(0.00376)	(0.00303)
Dividends per share (2018)		– 0.0543	– 0.0783**
		(0.0334)	(0.0298)
$\beta_{Excess-return-factor}$			– 0.224**
			(0.0955)
$\beta_{SMB-factor}$			– 0.0269
			(0.0630)
$\beta_{HML-factor}$			0.149**
			(0.0715)
$\beta_{Aggregate-Liquidity}$			– 0.433**
			(0.238)
$\beta_{Innovations-in-Liquidity}$			– 0.170
			(0.180)
$\beta_{Traded-liquidity-factor}$			– 0.0111
			(0.0999)
$\beta_{sentiment}$			– 1.883***
			(0.568)
β_{VIX}			52.37**
			(20.84)
Constant	– 4.034***	– 4.288***	– 4.080***
	(0.352)	(0.481)	(0.466)
F	25.83	17.38	12.02
N	282	282	282

Note: Standard errors in parentheses.* $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table A3. Robustness check: log(bond PageRank) with log(stock PageRank) for varying time periods with maximum number of firms available with matching data.

	Dependent variable:				
	log(bond PageRank)				
	2013–2015 (1)	2013–2016 (2)	2013–2017 (3)	2013–2018 (4)	2013–2018 (baseline)
log(stock PageRank)	– 0.0320	0.144*	0.134*	0.148**	0.150**
	(0.0795)	(0.0816)	(0.0797)	(0.0593)	(0.0579)
Constant	– 6.426***	– 5.297***	– 5.303***	– 5.186***	– 4.982***
	(0.489)	(0.510)	(0.499)	(0.377)	(0.357)
Observations	351	351	351	351	282
F	0.162	3.112	2.839	6.229	6.741
Adjusted R^2	– 0.002	0.010	0.008	0.014	0.019

Notes: Relationship holds for 4 years to 6 years horizon (data is incomplete beyond 6 years). For smaller sample (three years; 2013-15), the time horizon is too short for correctly estimating GCN. Errors have been clustered at two-digits SIC codes. Standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table A4. Robustness check: log(bond PageRank) with log(stock PageRank) for different lag orders used in evaluation of Granger-causality.

	Dependent variable:		
	log(bond PageRank)		
	Lag 1 (1)	Lag 2 (baseline)	Lag 3 (3)
log(stock PageRank)	– 0.00326	0.150**	0.146***
	(0.0548)	(0.0579)	(0.0515)
Constant	– 5.906***	– 4.982***	– 5.011***
	(0.347)	(0.357)	(0.296)
Observations	282	282	282
F	0.00354	6.741	8.089
Adjusted R^2	– 0.004	0.019	0.017

Notes: Lags greater than equal to 2 produce consistent results. Errors have been clustered at two-digits SIC codes. Standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table A5. Robustness check: log(bond PageRank) with log(stock PageRank) for different maturities and types of bonds.

	Dependent variable:			
	log(bond PageRank)			
Maturity	10 years (baseline)	4–10 years (baseline+)	> 10 years (baseline+)	10 years (baseline+)
log(stock PageRank)	0.150**	0.177***	0.136*	0.185***
	(0.0579)	(0.0492)	(0.0734)	(0.0568)
Constant	– 4.982***	– 5.104***	– 5.076***	– 5.000***
	(0.357)	(0.308)	(0.446)	(0.356)
Observations	282	397	275	369
F	6.741	12.98	3.429	10.64
Adjusted R^2	0.019	0.020	0.009	0.023

Notes: Results are robust in both cases. Errors have been clustered at two-digits SIC codes. The set of firms in ‘baseline+’ include non-convertible bonds in addition to those in the baseline model. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A6. Regression Results: log(bond PageRank) with log(stock PageRank) derived from residuals of regression of stock returns on the three Fama-French factors.

	Dependent variable:	
	log(bond PageRank)	
	(baseline)	(residual-based regression)
log(stock PageRank)	0.150**	
	(0.0579)	
log(stock PageRank$_{residuals}$)		0.198**
		(0.0837)
Constant	– 4.982***	– 4.729***
	(0.357)	(0.495)
Observations	282	282
F	6.741	5.608
Adjusted R^2	0.019	0.013

Notes: We conclude that aggregate factors in the stock market do not explain the relationship, implying that the vulnerability is a firm-level characteristic. Errors have been clustered at two-digits SIC codes. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A7. Robustness check: Baseline results along with GARCH-adjusted returns and PageRank derived from return-correlation adjacency matrix.

	Dependent variable:		
	log(bond PageRank)		
	(baseline)	(volatility correction)	(comovement-based)
log(stock PageRank)	0.150**		
	(0.0579)		
log(stock PageRank)$_{GARCH-adjusted}$		0.118*	
		(0.0650)	
log(stock PageRank)$_{correlation-matrix}$			0.153**
			(0.0667)
Constant	– 4.982***	– 5.168***	– 4.809***
	(0.357)	(0.387)	(0.372)
Adjusted R^2	0.019	0.011	0.021
F	6.741	3.320	5.246
Observations	282	282	282

Notes: Results are robust with respect to latent volatility adjustment and comovement measures. Errors have been clustered at two-digits SIC codes. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A8. Regression Results: Relationship of CoVaR for various return percentiles for the baseline sample and MES measure with log(stock PageRank).

	Dependent variable:				
	$\text{CoVaR}^i_{0.1}$ (1)	$\text{CoVaR}^i_{0.25}$ (2)	$\text{CoVaR}^i_{0.75}$ (3)	$\text{CoVaR}^i_{0.9}$ (4)	MES (5)
log(stock PageRank)	0.0400***	0.0211***	– 0.0103***	– 0.0119***	0.00005
	(0.0079)	(0.0046)	(0.0036)	(0.0068)	(0.0009)
Constant	– 1.0974***	– 0.5115***	0.5167***	0.9740***	0.0222***
	(0.0464)	(0.0268)	(0.0209)	(0.0397)	(0.0051)
Observations	282	282	282	282	282
R^2	0.0830	0.0702	0.0288	0.0108	0.00001
Adjusted R^2	0.0797	0.0669	0.0253	0.0073	– 0.0036

Notes: Consistent with the literature, we see that different systemic risk and vulnerability measures do not correlate with each other. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A9. Cross-correlation table – Stocks.

Variables	PageRank	Closeness	Betweenness	In-degree	Out-degree	Eigenvector
PageRank	1.000					
Closeness	0.726	1.000				
Betweenness	0.559	0.454	1.000			
In-degree	0.802	0.814	0.497	1.000		
Out-degree	– 0.114	– 0.136	0.515	– 0.148	1.000	
Eigenvector	0.801	0.612	0.450	0.878	– 0.171	1.000

Table A10. Cross-correlation table – Bonds.

Variables	PageRank	Closeness	Betweenness	In-degree	Out-degree	Eigenvector
PageRank	1.000					
Closeness	0.898	1.000				
Betweenness	0.614	0.543	1.000			
In-degree	0.876	0.989	0.527	1.000		
Out-degree	– 0.225	– 0.299	0.291	– 0.326	1.000	
Eigenvector	0.921	0.987	0.566	0.985	– 0.258	1.000

Table A11. Comparison of clusters in stocks and bonds for k = 2, 3, 4 and 5.

	Stocks				Bonds		
Clusters	#	$N_{\#}$	$E(\log(PR))$	$E(\log(mcap))$	#	$N_{\#}$	$E(\log(PR))$
$k = 2$	**2**	178	− 5.9904	17.527	**1**	123	− 5.5422
	1	104	− 5.6296	15.172	**2**	159	− 6.1115
$k = 3$	**2**	64	− 5.6045	14.596	**1**	73	− 6.1623
	1	73	− 6.1746	18.409	**3**	67	− 5.4619
	3	145	− 5.8093	16.688	**2**	142	− 5.8988
$k = 4$	**3**	57	-5.6665	14.480	**2**	108	− 6.2516
	4	80	− 5.3193	16.488	**3**	54	− 6.1055
	2	56	− 6.0619	18.641	**1**	46	− 5.5878
	1	89	− 6.3345	16.960	**4**	74	− 5.2908
$k = 5$	**5**	72	− 6.1636	17.624	**1**	33	− 6.0884
	3	52	− 5.5919	14.395	**2**	74	− 6.1670
	1	57	− 5.1383	16.601	**3**	43	− 5.5788
	4	32	− 6.1042	19.074	**4**	83	− 6.1326
	2	69	− 6.2174	16.284	**5**	49	− 5.0461

Notes: Clusters are identified by notation # and the number of firms in the corresponding cluster is given by $N_{\#}$. $E(log(PR))$ and $E(\log(mcap))$ denote PageRank center in terms of log of PageRank and average of log(market capitalization) of the clusters members respectively. Negative relationship between $E(log(PR))$ and $E(\log(mcap))$ is evident. See also figure A1 for visualization of the results.

Appendix 3. Non-parametric analysis

Table A12. Regression Results: log(bond PageRank) with log(stock PageRank) covering the Global Financial Crisis (GFC) period from 2007 to 2010.

	Dependent variable:	
	log(bond PageRank)	
	(2007–2010)	(2009–2012)
log(stock PageRank)	– 0.0148	0.166**
	(0.0698)	(0.0773)
Constant	– 5.300**	– 4.379**
	(0.387)	(0.431)
adj. R^2	– 0.006	0.028
F	0.0452	4.592
N	160	160

Notes: The period from 2009 to 2012 covers the post-crisis period. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A13. Regression results: log(bond PageRank) with log(stock PageRank) covering the Covid-19 crisis period in 2020.

	Dependent variable:	
	log(bond PageRank)	
	(2015–2018)	(2017–2020)
log(stock PageRank)	– 0.0184	– 0.0324
	(0.0600)	(0.0585)
Constant	– 6.291***	– 6.608***
	(0.379)	(0.369)
adj. R^2	– 0.002	– 0.002
F	0.0940	0.307
N	388	388

Standard errors in parentheses * $p < .1$, ** $p < .05$, *** $p < .01$.

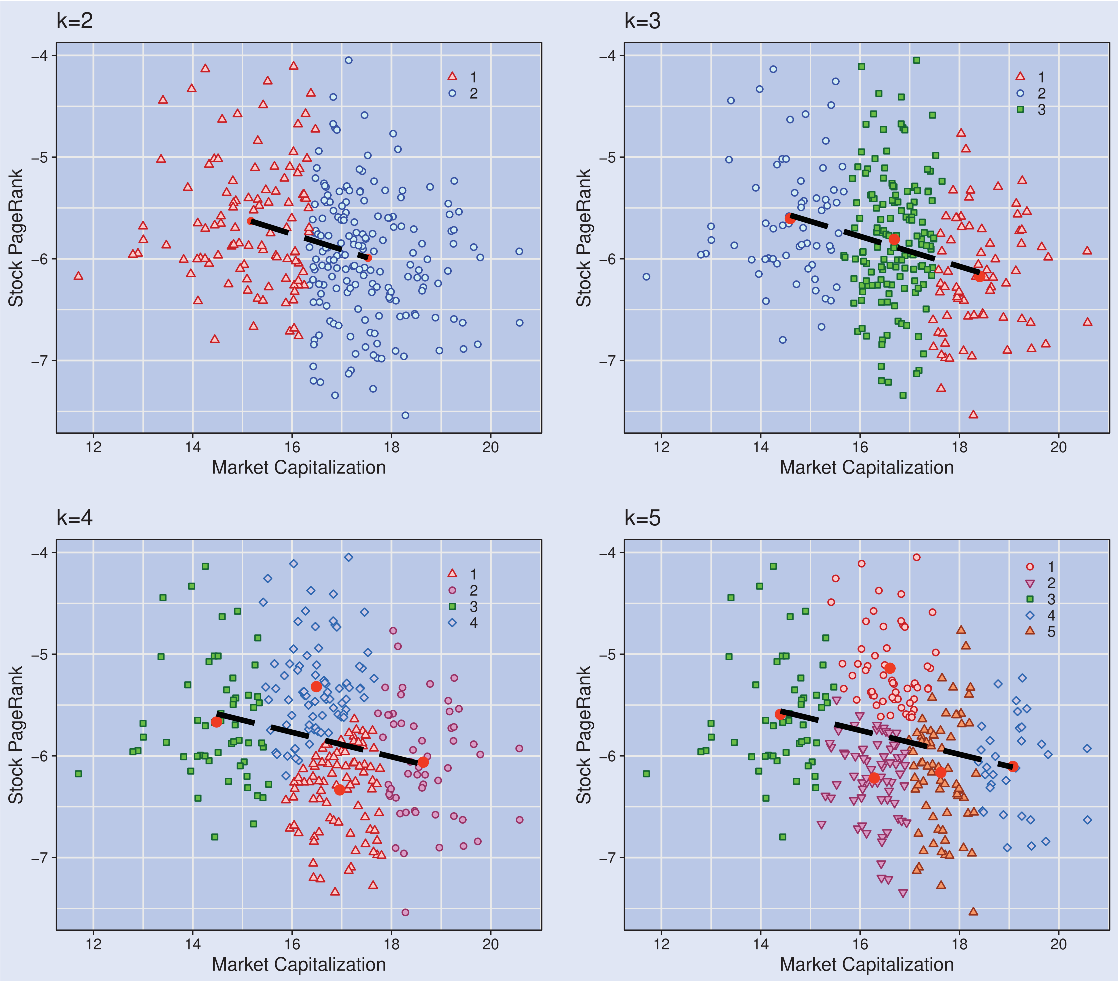

Figure A1. Clustering (k-means) of firms with respect to their stock PageRanks and market capitalization. The y-axis plots log of stock PageRank and the x-axis plots log of market capitalization (for year 2018) of the firms. We have also plotted cluster-wise average sizes (log of market capitalization) and PageRanks (red filled circles) and a linear fit is shown to capture the negative relationship (black dashed line) indicating that larger firms exhibit lower vulnerabilities.

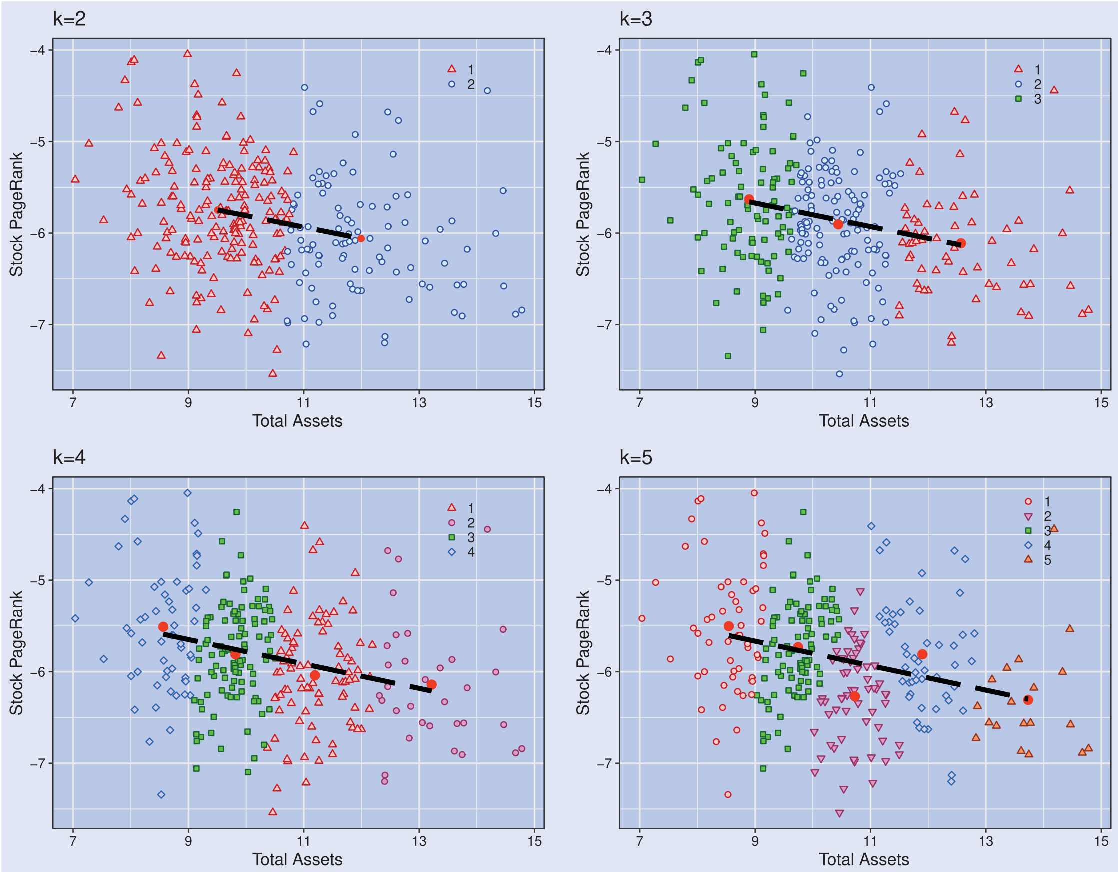

Figure A2. Clustering (k-means) of firms with respect to their stock PageRanks and market capitalization. The y-axis plots log of stock PageRank and the x-axis plots log of total assets (for year 2018) of the firms. We have also plotted cluster-wise average sizes (log of total assets) and PageRanks (red filled circles) and a linear fit is shown to capture the negative relationship (black dashed line) indicating that larger firms exhibit lower vulnerabilities.