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

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**W.P. No. 2020-06-02**
June 2020



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# 'Too central to fail' firms in bi-layered financial networks: Evidence of linkages from the US corporate bond and stock markets[1]

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**Abstract**

Complex mutual dependencies of asset returns are recognized to contribute to systemic risk. A growing literature emphasizes that identification of vulnerable firms is a fundamental requirement for mitigating systemic risk in a given asset market. However, in reality, firms are generally active in multiple asset markets with potentially different degrees of vulnerabilities in different markets. Therefore, to assess combined risks of the firms, we need to know how systemic risk measures of firms are related across markets? In this paper, we answer this question by studying US firms that are active in both stock as well as corporate bond markets. The main results are twofold. One, firms that exhibit higher systemic risk in the stock market also tend to exhibit higher systemic risk in the bond market. Two, systemic risk within an asset category is related to firm size, indicating that 'too-big-to-fail' firms also tend to be 'too-central-to fail'. Our results are robust with respect to choice of asset classes, maturity horizons, model selection, time length of the data as well as controlling for all major market-level factors. These results have prominent policy implications for identification of vulnerabilities and targeted interventions in financial networks.

**Keywords:** Network centrality, Risk management, Systemic risk, Stocks and bonds, Too central to fail

**JEL Codes:** G01, G32, G17, G18

[1]We are grateful to seminar participants at IIM Ahmedabad for useful feedback. This research was partially supported by institute grant, IIM Ahmedabad. All remaining errors are ours.

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> Without the bailout, AIG's default and collapse could have brought down its counterparties, causing cascading losses and collapses throughout the financial system.
>
> The Financial Crisis Inquiry Report (2010)

# 1 Introduction

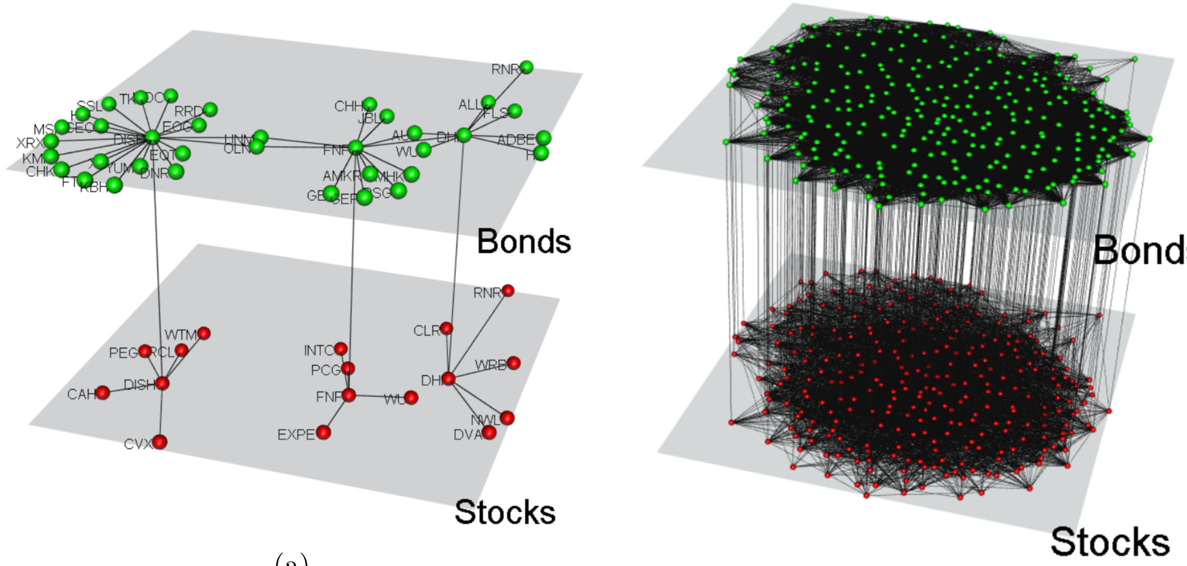
In the aftermath of the 2007-09 financial crisis, interconnectedness in the economic and financial systems has come under scrutiny as one of the leading potential causal mechanisms for diffusion of distress from local neighborhood of the epicenter, leading to a system-wide impact. The concept of *systemic risk* has become an important tool to quantify vulnerability of firms in network. A sudden change in the nature and degree of connectedness within a network leads to lesser chances of containment of a shock and higher chances of distress spillover arising out of a localized, idiosyncratic shock. Proposed mechanisms of such spillover due to the nature of connectivity range from insolvency spillovers (Gai and Kapadia (2010); Elliott et al. (2014); Eisenberg and Noe (2001)), volatility spillover (Diebold and Yilmaz (2015)), common exposure to liquidity shocks (Allen and Gale (2000)) to informational channels (Ahnert and Georg (2018); Acharya and Yorulmazer (2008)) among others. Multiple episodes of large scale financial distress, e.g. default of the insurance giant AIG and bankruptcy of Lehman Brothers, brought forward a complementary theme of inquiry viz. how to identify epicenters of distress and limit the damages? Three major themes have evolved to collectively address such *Systematically Important Firms* or SIFs: too big to fail, too connected to fail and too central to fail (Yun et al. (2019)) entities within a single network.

However, more often than not, firms are embedded in more than one networks with different sets of interconnections leading to different sets of SIFs. For management of systemic risks, a crucially important question is whether a firm that is systematically important in one network, is also systematically important in other networks? The potential consequences are very different between two scenarios as described below. To conceptualize, let us consider a set of firms embedded in two networks. Let us imagine that under the first scenario, SIFs in network number one are also the SIFs in network number two. This correlation would imply that targeted and symmetric interventions across the networks are useful to curb systemic risk. Under the second scenario, the SIFs are different in two networks. This lack of correlation would imply that a targeted intervention in one network will not reduce systemic risk in the other network. Consequently, different measures are required to curb risk in two different markets. Naturally, from the view-point of a social planner who engages in interventions which come at a cost, the first scenario would dominate the second in terms of social welfare. Although there have been some recent attempts to quantify the relationship between multiple levels of interconnectivity (e.g. Perillo and Battiston (2018)), the nature of relationship between systemic risks across networks remains unexamined. Thus targeted interventions have often been made (as described for example, in the quote from The Financial Crisis Inquiry Report (2010)) without a complete mapping of linkages across markets.

In this paper, we ask the following question: Are systematically important firms in one asset market also systematically important in other asset markets? In other words, are vulnerabilities (or resiliences) of firms correlated across markets? To answer this question, 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 Fig. 1. Based on a standard measure of systemic risk, we estimate *rank* of firms in the two return networks where a higher rank denotes higher vulnerability and higher contribution to systemic risk. Our main result is that the rank of firms in the stock network is strongly correlated with the rank of firms in the bond network. This finding is robust with respect to a large variety of controls (inclusive of but not limited to the impacts of Fama-French factors, sentiment, aggregate volatility and money market factors), time horizons and types of assets. We instrument systemic risk in stock market by size (total market capitalization) and profitability proxies (earnings and dividends per share) of firms and quantitatively similar results prevail. Finally, we apply non-parametric clustering techniques borrowed from physical science literature to complement and bolster the above analysis.

At the outset, we note that 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, viz. investors risk appetite (bond holders would be more averse to downside risk than stock holders), 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 there are no a priori reasons to suspect that the firms which are prone to systemic risk in the bond market are necessarily prone to systemic risk in the stock market as well. However, both bond and stock returns contain formation about firm fundamentals. Thus potentially there is a linkage, which we explore and establish in this paper.

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 firms who are active in both the markets. Also, to maintain parity over maturity periods, we have considered bonds with a ten-year maturity period, which constitutes 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 Sec. 2). For constructing the network linkages, we follow the literature on *Granger Causal Networks* (Yun et al. (2019); Billio et al. (2012)) which is constructed from bi-variate granger-causality tests between all pairs of firms. We define systemic risk by calculating PageRank centrality (Page et al. (1999)) which accounts for both 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 based on spectral decomposition. PageRank is based on a transformation of eigenvector centrality that captures the in-degrees which is




(a) (b)

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 5 in the Appendix). 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.

important for quantifying *vulnerability* in the context of systemic risk and also, allows for tuning of dampening effects arising out of local and global neighborhoods in the network.

We have constructed firm-specific variables that capture responsiveness to market sentiments, 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 systemic risk in the bond market. But the stock market systemic risk is explained by size and profitability of the firm. 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 Tobias and Brunnermeier (2016)) and MES (marginal expected shortfall; proposed by Acharya et al. (2017)) shows that three indices of systemic risk do not convey the same information, a finding consistent with Yun et al. (2019). Finally, we use $k$-means clustering borrowed from physical science literature (Hartigan (1975)) 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 literature is threefold. The first one is of theoretical nature. we establish that systemic risk can be concurrently analyzed in multi-layered financial markets. We use the growing field 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)), information diffusion in investors' network (Baltakys et al. (2018)), credit networks across financial firms (Luu and Lux (2019)) among others. Our work directly brings the analysis of systemic risk 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 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. Based on the definition of DebtRank, Battiston et al. (2012) 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, showed that the probability of a financial contagion can be very low; however, conditional on contagion occurring, there could a 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 (we have utilized this connection in our IV estimation), 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); 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 comovements (Cappiello et al. (2006); Connolly et al. (2005)). As opposed to the above literature which typically analyzes dynamics of corporate equities and government-issued bonds, we analyze a set of firms which are active in both markets simultaneously and establish that the systemic risk components in both markets are related. As far as we know, this is a novel analysis in terms of linkage between networks constructed form different asset classes.

Rest of the paper is organized as follows. In Sec. 2 we describe the data along with the procedure for sample selection. Next, we describe the construction of measure of systemic risk from Granger-Causal Network (Sec. 2.3). In Sec. 3, we analyze the relationship between systemic risks of firms embedded in the stock return network vis-a-vis systemic risks of the same set of firms in the bond return network. All robustness checks have been presented in Sec. 4 and Sec. 5 describes the non-parametric analysis based on $k$-means clustering. Sec. 7 summarizes and concludes the paper.

# 2 Empirical data and methodology

In this section, we provide 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 case of the stock market, we utilize the notation $W_s$, and in case of the bond market, we use $W_b$. The main specification that we will estimate in Sec. 3 is how systemic risk in the bond market is related to the systemic risk in the stock market (Eqn. 6). Before getting to the main specification we define the systemic measures below along with the instruments for the stock market systemic risk.

## 2.1 Data description: Sample selection

Here, we detail the steps taken in the selection process of the sample of stocks and bonds for analysis. We have used the services of TRACE[5] system for obtaining bond prices and the CRSP[6] database for stock prices, accessed through Wharton Research Data Services (WRDS).[7] 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 (2013-2018) 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 within 2017 and 2023 for our baseline model, as they are typically the most liquid bonds. In the section on robustness, we have considered bonds with less than 10 years as well as more than 10 years' maturity. There are two reasons that motivated us to consider bonds with 10 years' maturity period in our baseline model. First, within the data, we observe that the 10 year bonds have been traded more frequently than others (shorter and longer term). This is consistent with the standard

[5]Website: https://www.finra.org/filing-reporting/trace
[6]http://www.crsp.org/
[7]https://wrds-www.wharton.upenn.edu/

features of the debt market. Secondly, we have excluded borrowing at the short end of the maturity spectrum in the baseline model as we want to focus on longer term expectation about the firms in a relatively more liquid market.[8]

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.

## 2.2 Return series construction

Each stock/bond 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).[9] The baseline regression consists of 282 firms (for details, see table 5 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 5) and therefore, we have to combine the corresponding multiple return series into one series so that we can uniquely define systemic risk for those firms in the bond market. Since we want to construct a single measure of systemic risk in the bond market, we took the first principal components of the set of bond returns issued by individual firms. For example, if a firm issues more than one bonds (like Amgen Inc or Bank of America Corp in table 5), 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, for such a firm 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. Equity return by construction is a single series, and therefore no such adjustment is required. After establishing the baseline results, we enlarge the class of bonds considered along with variation in maturity periods, in the section on robustness checks.

[8] Guedes and Opler (1996) empirically documented that while firms with speculative-grade credit ratings typically borrow at the middle of the maturity spectrum, large firms with investment-grade credit rating borrow at the long end (and also short end).

[9] 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.

## 2.3 Measuring systemic risk from the stock and bond returns

In this section, we define systemic risk following Yun et al. (2019). To construct the measure of systemic risk, 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 systemic risk. 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 assets and their causal relationship (Yun et al. (2019), Billio et al. (2012)). Linear least squares predictors are used to operationalize the test (see Granger and Newbold (2014)). We perform a bivariate vector autoregression estimation of the following set up:

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

where the coefficients $A_{11}$,$A_{12}$,$A_{21}$,$A_{22}$ of 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. A Wald test is incorporated in this linear setup to test for Granger-causality. The null hypothesis that $Y$ does not Granger-cause $X$ is rejected if the coefficients of the lag polynomial $A_{12}$ are jointly significantly non-zero. Feedback exists (bi-directional Granger-causality) exists if the coefficients of both $A_{12}$ and $A_{21}$ are jointly significantly non-zero. This sense of direction of Granger-causality enables us to formulate a directed network from the return series of stocks and bonds.

In order to construct a Granger Causal Network (GCN) of one asset type (stocks or bonds), 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 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 estimating Eqn. 2 with a lag polynomial of order two, for stocks and bonds, respectively. In Sec. 4, we discuss the robustness of the results when we relax the lag order choice.

### 2.3.2 Quantifying systemic risk 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 which is also defined as systemic risk in the literature (Yun et al. (2019)). 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 $\Gamma$ 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:

$$PageRank(i) = \frac{(1-d)}{N} + d \sum_{j \in \mathcal{N}^i} \omega_{ij} PageRank(j), \tag{3}$$

where $i \neq j$, $d$ is the dampening factor[10] and $\omega_{ij}$ is the weight associated with the number of outgoing links from node $i$ to node $j \in \mathcal{N}^i$.

In our case, the network is produced by Granger causality, i.e. $\omega_{ij}$ denotes Granger causality from asset $i$ to $j$ as defined above in Sec. 2.3.1. An asset $i$ is more vulnerable than $j$ if $PR(i) > PR(j)$. 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 than others and/or its return is explained by other vulnerable assets.

[10] 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 Eqn. 3 is clearly a fixed point of the recursion which can be solved either iteratively staring from some initial guesses, or algebraically at the fixed point itself.

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 exptected 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

[a] http://people.stern.nyu.edu/jwurgler

[b] https://faculty.chicagobooth.edu/lubos-pastor/data

## 2.4 Bond market control variables

In this section, we list the variables that are used in constructing control variables for explaining 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 which draws on analysis of 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 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.

$$Bond\ returns_{it} \; = \; \beta_0 + \beta_i Y_t + \epsilon_{it}, \quad i = 1, \ldots, \text{N}; \;\; t = 1, \ldots, \;\; \text{T} \tag{4}$$

where $Y$ represents the explanatory variables considered, $\beta_i$ 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 stock market systemic risk

In the following we list the instrumental variables for the stock market systemic risk used in our analysis. The main idea is that 'too central to fail firms' are essentially 'too big to fail' firms. Therefore, we use size variable as the main instrument for (the inverse of) systemic risk. 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.

Firm fundamentals considered are directly linked with the firm's participation in the stock market. It is well known that cross-section of stock returns are explained by the three Fama-French factors (Fama and French (1992)), indices like the Volatility Index, or VIX created by Chicago Board Options Exchange (CBOE)[11], Baker-Wurgler sentiment index[12], and Pastor-

[11] 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 resilience of stocks.

[12] Baker and Wurgler (2006, 2007) proposed an index of investor sentiment based on first principal component of five (standardized) sentiment proxies where each of the proxies has first been orthogonalized with

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 |
| $\beta_{VIX}$ | 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 |

Stambaugh liquidity indices[13]. 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.

$$Stock\ returns_{it} \ = \ \beta_0 + \beta_i Z_t + \epsilon_{it}, \quad i = 1, \ldots, \mathrm{N}; \ t = 1, \ldots, \ \mathrm{T} \tag{5}$$

where $Z$ represents the explanatory variables considered. $\beta_i$ represents the sensitivity of returns to the variables. In this multivariate setup, we obtain $\beta_{Excess-return-factor}$, $\beta_{SMB-factor}$, $\beta_{HML-factor}$, $\beta_{VIX}$, $\beta_{sentiment}$, $\beta_{Aggregate-Liquidity}$, $\beta_{Innovations-in-Liquidity}$ 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.

An explanation for the choice of full set of instruments is given in section 3.1. 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 5).

# 3 Systemic risk: 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:

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

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-Piazessi factor, term spread and default spread. Our main interest is in the coefficient $\beta_{sr}$ representing the relationship between two systemic risk measures. A positive relationship would imply that high systemic risk in the stock market is related to high systemic risk in the bond market. In the following, we first elaborate on simple regression results and next, we provide results obtained from instrumental variable regressions.

The main results are summarized in table 3. Model (1) simply regresses $log(bond\ PageRank)$ on $log(stock\ PageRank)$. The positive and significant relationship indicates that if a firm

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 Eqn. (3) of the paper.

[13] Pástor and Stambaugh (2003) find that cross-section of expected stock returns are 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 Eqn. (8) in the paper) and traded liquidity factor(LIQ_V, 10-1 portfolio return) respectively

has higher a systemic risk in the stock network, it is more likely to have higher systemic risk in the bond network as well. In particular, given the log-log specification, one percent increase in systemic risk in the stock market for a firm is associated with 0.15 percent increase in the systemic risk in the bond market.[14] In the remaining models, we sequentially add control variables and the estimates are quite robust. None of the responsiveness parameters seems to contain explanatory power for systemic risk.

## 3.1 Effect of firms' fundamentals: IV results

Given the simultaneous estimation of the stock and bond market systemic risk, there is a potential for endogeneity in the relationship. Here we instrument stock centrality by firms' fundamentals, and we show that the same set of results hold. The set of instruments 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.

Here we explain our choice of instruments. Stock market capitalization is an obvious indicator of size, that would potentially directly impact systemic risk of the firm in the stock market. This conjecture is fundamentally based on the idea that 'too big to fail' firms tend to be 'too central to fail'. There is no a priori reason as to why market capitalization would directly impact systemic risk in the bond market except through affecting the systemic risk in the stock market. We have calculated Fama-French $\beta$'s since they are known to impact the cross section of stock returns (see Petkova and Zhang (2005)). Additionally, $\beta_{VIX}$ and $\beta_{sentiment}$, the sensitivity of the stock returns to movement in the VIX index and overall market sentiment, which are known to impact the cross section of stock returns (see Baker and Wurgler (2006); Ang et al. (2006)). Finally, liquidity risk factors are known to explain the cross sectional variation of stock returns (see Pástor and Stambaugh (2003)). The idea is a firm with higher exposure to the aggregate volatility risk, is also more vulnerable to the return movements of other firms in the network. Similarly, for sentiment and liquidity risk.

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 alone explains most of the variability in the systemic risk measure. The main result is quite robust that stock PageRank is strongly related to bond PageRank. However, as we incorporate other control variables, the first stage $F$-stat goes down.

[14] Here we note that there are firms who have issued multiple bonds and we have considered the first principle component of the bond returns for our calculations as described in Sec. 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 retains 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 $\beta_{sr}$ in Eqn. 6.

Table 3: Regression results of log(bond PageRank) on log (stock PageRank) with covariates. The covariates we have considered are responsiveness of stocks to money market, medium and long term spreads, Cochrane-Piazzesi factors, term and default spreads. The relationship between PageRanks is stable and incorporating the responsiveness coefficients does not impact the relationship. Errors have been clustered at two-digits SIC codes.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | log(bond PageRank) | | | |
| | (1) | (2) | (3) | (4) |
| log(stock PageRank) | 0.150** | 0.152** | 0.152** | 0.151** |
| | (0.0579) | (0.0591) | (0.0591) | (0.0596) |
| $\beta_{\Delta mmmf}$ | | 561.5 | 541.8 | 373.9 |
| | | (337.2) | (338.1) | (353.1) |
| $\beta_{on-off-spread-5years}$ | | -0.209 | -0.264 | -0.279 |
| | | (0.189) | (0.218) | (0.260) |
| $\beta_{on-off-spread-10years}$ | | -0.0927 | -0.171 | -0.132 |
| | | (0.150) | (0.202) | (0.289) |
| $\beta_{cp-factor}$ | | | -3.496 | -0.325 |
| | | | (4.373) | (31.13) |
| $\beta_{term-spread}$ | | | | 4.264 |
| | | | | (13.08) |
| $\beta_{default-spread}$ | | | | -2.039 |
| | | | | (1.880) |
| Constant | -4.982*** | -4.952*** | -4.947*** | -4.948*** |
| | (0.357) | (0.366) | (0.367) | (0.370) |
| Observations | 282 | 282 | 282 | 282 |
| F | 6.741 | 3.270 | 2.588 | 5.360 |
| Adjusted $R^2$ | 0.019 | 0.024 | 0.021 | 0.020 |

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 4: IV regression results of log(bond PageRank) on log (stock PageRank) with covariates. 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 ($\beta$ 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. Errors have been clustered at two-digits SIC codes.

| | *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) |
| $\beta_{\Delta mmmf}$ | | | | 285.3 | 303.1 | 335.9 |
| | | | | (573.5) | (506.6) | (398.3) |
| $\beta_{on-off-spread-5years}$ | | | | 0.0366 | -0.0268 | -0.144 |
| | | | | (0.325) | (0.275) | (0.241) |
| $\beta_{on-off-spread-10years}$ | | | | 0.240 | 0.165 | 0.0273 |
| | | | | (0.321) | (0.294) | (0.275) |
| $\beta_{cp-factor}$ | | | | 3.267 | 2.547 | 1.213 |
| | | | | (39.08) | (35.03) | (29.89) |
| $\beta_{term-spread}$ | | | | 5.884 | 5.559 | 4.957 |
| | | | | (18.11) | (15.94) | (12.95) |
| $\beta_{default-spread}$ | | | | -1.153 | -1.331 | -1.660 |
| | | | | (2.448) | (2.197) | (1.833) |
| 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 |

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

The effect of firm size on systemic risk is intuitive. A larger firm would be less prone to systemic failure compared to a small firm, controlling for all other factors. This indicates that 'too-big-to fail' firms might also be 'too-central-to-fail'. Therefore, these two concepts may be more related than usually thought of (Yun et al. (2019)).

# 4 Robustness of systemic risk 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 Variation in time horizon of estimation

Next, we check how robust is the relationship with respect to varying time-length of the sample. Table 6 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 collected bond and stock price data for the largest set of firms available, which turns out to consist of 351 firms. Then we regress log of bond PagRank on log of stock PageRank for four consecutive windows with increasing lengths, starting from 2013-15 (three years) to 2013-18 (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 is seen in table 6, 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 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 2007-09 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.

## 4.2 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 viz. 1, 2 and 3. The results reported in table 7 indicate that the relationship persists for lag orders of 2 and 3.

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

## 4.3 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 5 for the CUSIP ids) and we find that the relationship between a firm's resilience 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 8, we have present 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.

## 4.4 Residual-based analysis after controlling for aggregate movements

One possibility is that the variation in the systemic risk 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 correlation between resilience of stocks and bonds exists even after controlling for common risk factors affecting stock returns, as shown in Table 9. The first column describes the results with residuals and the second column describes the results with the baseline scenario (equivalent of column 1 in table 3).

## 4.5 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 because of 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

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

and $\xi$ 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 10 presents the baseline and the GARCH-adjusted results. We observe that the result persists albeit with slightly smaller magnitude of the coefficient.

We have also analyzed if the result holds with respect to comovement matrix instead of the lagged comovement analysis (Granger causal network represents lagged movements). Therefore, we constructed simplex correlation matrices and the corresponding PageRank vectors. These vectors do not have the same interpretation of systemic risk as we have followed so far. Instead, these represent contribution of each asset to the dominant eigenvector (if we strictly consider the interpretation of eigenvector centrality; PageRank is a function of eigenvector centrality). We see in table 10 that even with comovement matrices, a similar relationship exists. Although it is not customary to define systemic risk through systemic risk on the comovement matrices, this result establishes that the relationship between PageRanks could also exist with zero lags between the asset returns. In our view, this result rather than substituting the central relationship, complements the same.

# 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 systemic risk 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. A survey on clustering approaches [Cai et al. (2016)] 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 viz. partitioning methods, density-based methods and data-stream clustering methods. The $k$-means clustering method [Hartigan (1975); Hartigan and Wong (1979)] 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 systemic risk 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 systemic risk) comprise firms with smaller average size. Both of these features would corroborate and complement the earlier findings in a non-parametric way.

Fig. 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 indicate 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 earlier observation in a regression framework. Therefore, even in a coarse-grained clustering set up, the same relationship prevails. For both the stock market and bond market, we present the number and identity (denoted by #) of the clusters, number of firms in the clusters ($N_{\#}$), the average PageRank ($E(PR)$) and average (log of) market capitalization ($E(mcap)$) in table 11.

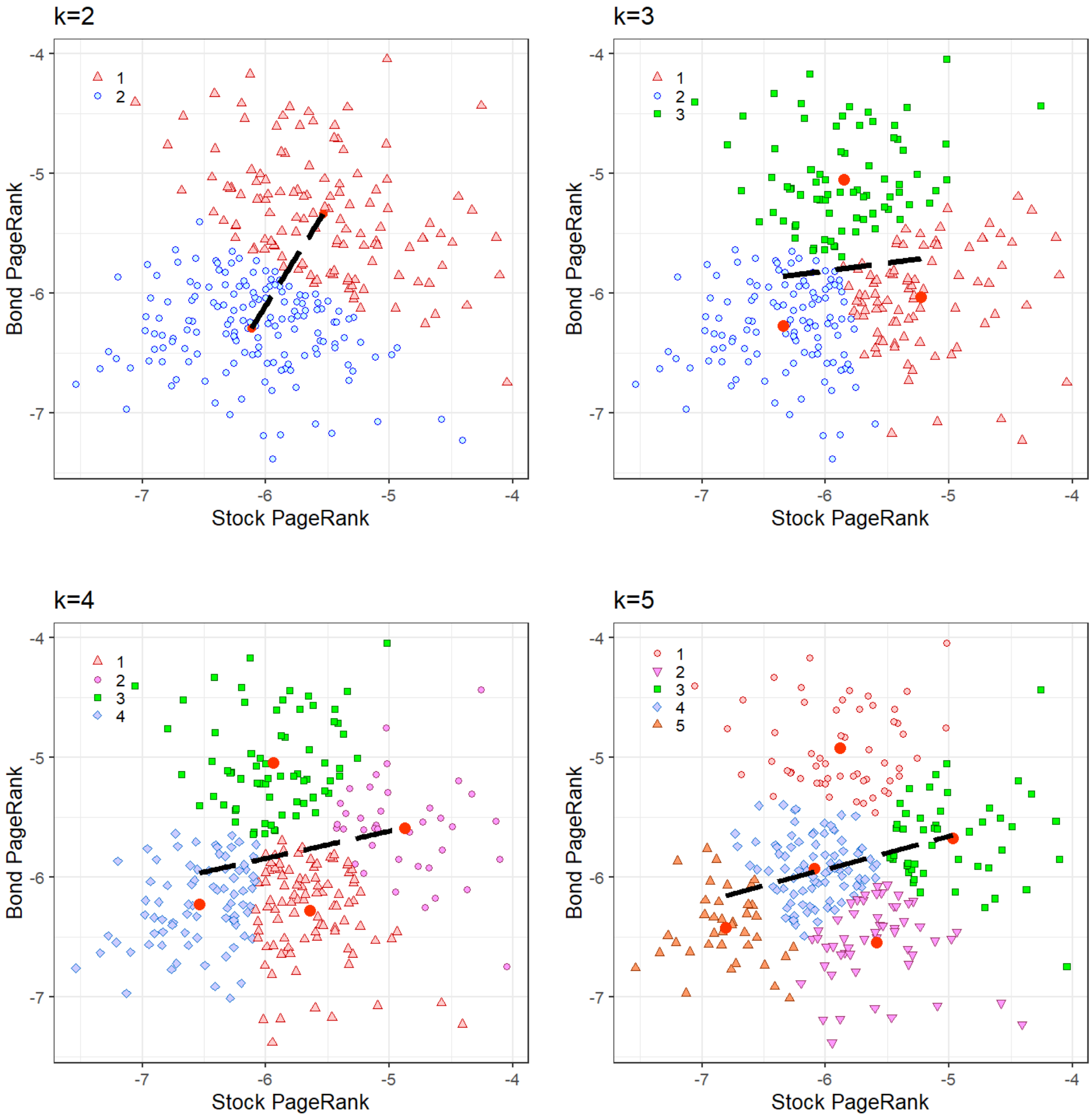



Figure 2: Clustering ($k$-means) of stocks and bonds with respect to their PageRanks. The $y$-axis plots log of bond PageRank and $x$-axis plots log of stock PageRank of the firm for reference. A linear fit across the cluster centers (red filled circles) is shown to capture the positive relationship (black dashed line) between bond and stock PageRanks. We conclude that systemic risk of firms in the bond market is positively related to systemic risk in the stock market.

# 6 Comparison with other measures of systemic risk: CoVaR and MES

In order to probe further into the nature of the systemic risk in the stock GCN, we compare the measure we have analyzed so far with other measures of systemic risk that exist in the literature. In particular, we have analyzed how closely is the stock PageRank related to conditional value at risk (CoVaR; Tobias 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 marginal expected shortfall for the stocks and perform univariate regression of log of stock PageRank on both CoVaR and MES. In table 12, 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 has been noted in the literature (Yun et al. (2019)).

# 7 Summary and conclusion

Quantification and management of systemic risk have received enormous attention in recent times, owing to the vulnerability of financial systems to crisis events. Typically, all existing measurements evaluate 'vulnerabilities' of the firms or its contribution to systemic risk, in terms of a network of assets. However, firms are generally active in multiple asset markets leading to a question of what is the nature of the relationship between systemic risks of the same set of firms active in different markets. There is no empirical answer to this question to the best of our knowledge.

In this paper, we consider firms in the US which are active both in the stock and the bond markets. Our main result is that a firm with a higher systemic risk in the stock market tends to exhibit higher systemic risk in the bond market as well. Additionally, 'too-big-to fail' firms also tend to be 'too-central-to fail'. Following the literature, we define systemic risk in terms of PageRank centrality of the Granger Causal Networks constructed from monthly equity and corporate bond return data. Our results are robust with respect to choice of the asset classes, maturity horizons, lags in Granger Causal Networks, time length of the data as well as controlling for all major market-level factors. Additionally, we present results based on coarse-grained clustering analysis which corroborates and complements the above findings.

Our findings should 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 positive spillovers in the complementary markets as well. Therefore, such a policy has unintended consequences with positive welfare effects. Finally, our dataset considers the post-financial crisis (2007-09) and pre-Covid-19 crisis (the global pandemic started in around February 2020) periods. It is possible that the relationship that we found here is time-varying. Extending the analysis in a larger set of markets covering data from crisis periods would shed more light on the nature and scope of such positive externalities.

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# Appendix

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.

# A 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 18.

Table 5: 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 |
| 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 |
| 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 |
| 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 |
| 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 |
| 193 | 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 |
| 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 |
| 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 |

# B Additional regression tables

Table 6: Robustness check: log(bond PageRank) with log(stock PageRank) for varying time periods with maximum number of firms available with matching data. 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.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | log(bond PageRank) | | | | |
| | 2013-15 (1) | 2013-16 (2) | 2013-17 (3) | 2013-18 (4) | 2013-18 (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 |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < .05$, $^{***}$ $p < 0.01$

Table 7: Robustness check: log(bond PageRank) with log(stock PageRank) for different lag orders used in evaluation of Granger-causality. Lags greater than equal to 2 produce consistent results. Errors have been clustered at two-digits SIC codes.

| | *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 |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < .05$, $^{***}$ $p < 0.01$

Table 8: Robustness check: log(bond PageRank) with log(stock PageRank) for different maturities and types of bonds. 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.

| | *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 |

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 9: Regression Results: log(bond PageRank) with log(stock PageRank) derived from residuals of regression of stock returns on the three Fama-French factors. We conclude that aggregate factors in the stock market do not explain the relationship, implying that the systemic risk is a firm-level characteristic. Errors have been clustered at two-digits SIC codes.

| | *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 |

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 10: Robustness check: Baseline results along with GARCH-adjusted returns and PageRank derived from return-correlation adjacency matrix. Results are robust with respect to latent volatility adjustment and comovement measures. Errors have been clustered at two-digits SIC codes.

| | *Dependent variable:* | | |
|---|---|---|---|
| | log(bond PageRank) | | |
| | (baseline) | (volatility correction) | (comovement-based) |
| log(stock PageRank) | 0.150** | | |
| | (0.0579) | | |
| $\log(\text{stock PageRank})_{GARCH-adjusted}$ | | 0.118* | |
| | | (0.0650) | |
| $\log(\text{stock PageRank})_{correlation-matrix}$ | | | 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 |

Standard errors in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < .05$, $^{***}\ p < 0.01$

# C Non-parametric Analysis

Table 11: Comparison of clusters in stocks and bonds for $k = 2$, 3, 4 and 5. 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 Fig. 3 for visualization of the results.

| **Clusters** | **Stocks** | | | | **Bonds** | | |
|---|---|---|---|---|---|---|---|
| | # | $N_{\#}$ | $E(log(PR))$ | $E(log(mcap))$ | # | $N_{\#}$ | $E(log(PR))$ |
| 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 |

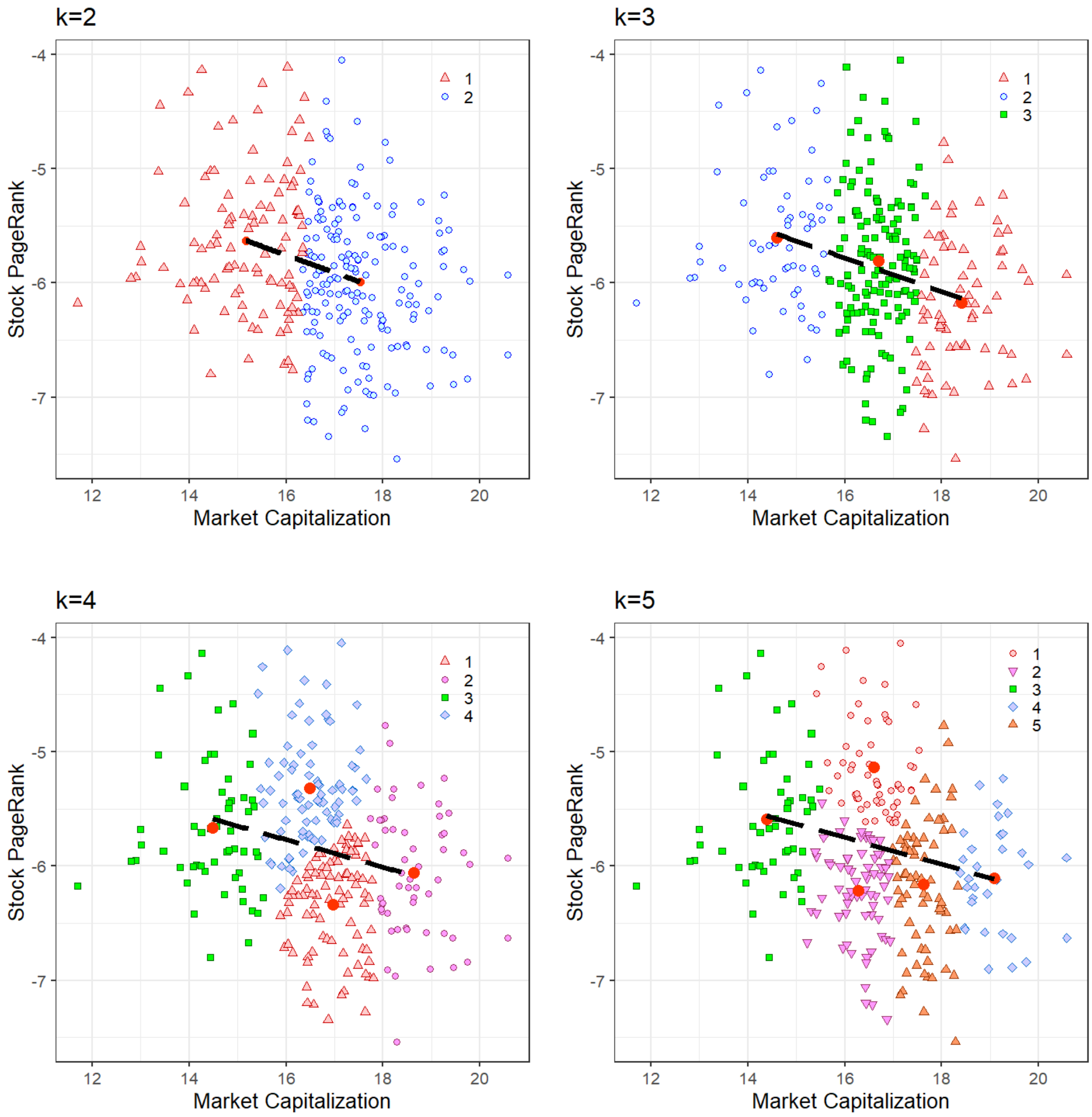


Figure 3: Clustering ($k$-means) of stocks and bonds with respect to their PageRanks. The $y$-axis plots log of market capitalization (for year 2018) of the firm for reference. We have also plotted the average size and PageRank for each cluster (red filled circles) and a linear fit is shown to capture the negative relationship (black dashed line). We conclude that larger firms exhibit lesser systemic risk.

Table 12: Regression Results: Relationship of CoVaR for various return percentiles for the baseline sample and MES measure with log(stock PageRank). Consistent with the literature, we see that different systemic rick measures do not correlate with each other.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | $\text{CoVaR}^i_{0.1}$ | $\text{CoVaR}^i_{0.25}$ | $\text{CoVaR}^i_{0.75}$ | $\text{CoVaR}^i_{0.9}$ | MES |
| | (1) | (2) | (3) | (4) | (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 |

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$