Modeling Contagion and Systemic Risk*

Daniele Bianchi† Monica Billio‡ Roberto Casarin‡ Massimo Guidolin§

Abstract

We model contagion in financial markets as a shift in the strength of cross-firm network linkages, and argue that this provide a natural and intuitive framework to measure systemic risk. We take an asset pricing perspective and dynamically infer the network structure system-wide from the residuals of an otherwise standard linear factor pricing model, where systematic and systemic risks are jointly considered. We apply the model to a large set of daily returns on blue chip companies, and find that high systemic risk occurred across the period 2001/2002 (i.e. dot.com bubble, 9/11 attacks, financial scandals, Iraq war), the great financial crisis, and the recent major Eurozone sovereign turmoil. Specifically, we show that few financial firms are key for systemic risk measurement. Such network centrality holds also at the industry level and does not depend on the relative market value of the financial sector. Finally, we show that our network-implied systemic risk measure provides an early warning signal on aggregate financial stress conditions.

Keywords: Financial Markets, Contagion, Networks, Systemic Risk, Asset Pricing

JEL codes: G12, G29

*This version: January 8, 2015. Comments are welcome. We are grateful to Peter Kondor and Neil Pearson for their helpful comments and suggestions. For financial supports, the authors thank the European Union, Seventh Framework Programme FP7/2007-2013 under grant agreement SYRTO-SSH-2012-320270, by the Institut Europlace de Finance, Systemic Risk grant, and by the Italian Ministry of Education, University and Research (MIUR) PRIN 2010-11 grant MISURA.

†University of Warwick - Finance Group, Coventry, CV4 7AL, UK. Daniele.Bianchi@wbs.ac.uk
‡Department of Economics, Università Cà Foscari, Venezia, Italy
§Department of Finance and IGIER, Bocconi University, Milan, Italy.
1 Introduction

Contagion appears central for systemic risk measurement and management in the aftermath of the recent financial crisis. Dramatic shocks to a single institution can quickly affect others operating in different markets, with different sizes and structures. Perhaps surprisingly, however, contagion and systemic risk remain rather elusive concepts, in many respects incompletely identified and poorly measured. In fact, anomalous patterns of cross-sectional dependence are difficult even to identify, much less characterize empirically.¹

In this paper, we address this situation by taking an asset pricing perspective and develop a unified framework to empirically identify channels of contagion in large dimensional time series settings, where sources of systematic and systemic risks are not mutually exclusive. Our methodology directly builds on the concept of network. Network analysis is omnipresent in modern life, from Twitter to the study of the transmission of virus diseases. Broadly speaking, a network represents the interconnections of a large multivariate system, and its graph representation can be used to study the properties of the transmission mechanism of exogenous shocks (e.g. patient zero in a virus disease). We remain agnostic as to how contagion arises; rather, we take it as given and seek how to capture it correctly for systemic risk measurement purposes.

For a given linear factor model, we measure contagion as a shift in the strength of the cross-firm network linkages, which are inferred system-wide on the covariance structure of the model residuals. This, not only allows disjoint sources of systematic and systemic risk coexist, but also is consistent with the common wisdom that posits contagion representing a significant increase in cross-sectional linkages across institutions/sectors/countries after a shock.² In particular, exposures of each firm to sources of systematic risk directly depends on the aggregate systemic risk measured through network connectedness.

This paper builds on a recent literature advocating the use of network analysis in economics and finance to make inference on the connectedness of institutions, sectors and countries, such


²See Forbes and Rigobon (2000) for a discussion of pros and cons of alternative definitions of contagion.
as Jackson (2008), Easley and Kleinberg (2010), Billio et al. (2012), Hautsch, Schaumburg, and Schienle (2012), Barigozzi and Brownlees (2013), Diebold and Yilmaz (2014), Timmermann, Blake, Tonks, and Rossi (2014) and Diebold and Yilmaz (2015). In particular, Billio et al. (2012) and Diebold and Yilmaz (2014) show that the strength of connectedness of financial institutions changed over time, substantially increasing across the recent great financial crisis. In the spirit of Diebold and Yilmaz (2014), we provide a unified framework to empirically measure contagion system-wide via Bayesian inference on cross-company linkages.

We take steps from this literature in several important directions. We propose a joint inference scheme on the network structure as a whole. Standard empirical methodologies are based on pairwise correlation and Granger causality measures to build the financial network. Recent evidence show that these pairwise measures can be biased making them of little value in a financial network context (see e.g. Forbes and Rigobon 2000, Ahelegbey, Billio, and Casarin 2014, and Diebold and Yilmaz 2014). In this paper, we make system-wide inference on a large dimensional network by simultaneously considering all of the possible linkages among institutions on the basis of an underlying undirected graphical model.3

Also, we fully acknowledge the fact that parameters are uncertain. Existing methodologies extract the network structure assuming the parameters of the model are constant in repeated samples. As a result, the derived inference is thus to be read as contingent on the econometrician having full confidence in his parameters estimates, which is objectively rarely the case. Moreover, alternative conceivable values of the parameters will typically lead to different networks. In this paper, we provide an exact finite-sample Bayesian estimation framework which helps generate posterior distribution of virtually any function of the model parameters, as well as posterior sufficient statistics for the underlying economic network. Such posterior estimates allow to test hypothesis on the nature and structure of the network linkages in a unified setting, which the earlier literature did not provide.

More prominently, we take into account the fact that contagion, and then systemic risk, is more a shift concept than a steady state (e.g. Forbes and Rigobon 2000). Indeed, Billio et al. (2012) and Diebold and Yilmaz (2014) provide evidence that connectedness of financial

---

institutions is stronger during financial turmoils. We take this evidence to suggest the presence of two distinct unobserved states driving network connectedness, therefore contagion and systemic risk. Consistently, we label the two latent states as “high” and “low” systemic risk, such that when the economy is a state of contagion indicates a high risk that a shock to a single firm can quickly affect the economic system as a whole.

Empirically, the paper focuses on a set of 100 blue-chip companies from the S&P100 Index. We consider those institutions with more than 15 years of historical data. We are left with 83 firms. Returns are computed on a daily basis, dollar-valued and taken in excess of the risk-free rate. The sample is 10/05/1996-31/10/2014 (4821 observations for each institution), for a total of more than 400,000 firm-day observations. Our emphasis on stock returns is motivated by the desire to incorporate the most current information for systemic risk measurement; stocks returns reflect information more rapidly than non-trading-based measures such as accounting variables, especially considering most of accounting information is not available on a daily frequency.

In the empirical analysis, we consider the impact of common sources of systematic risk such as the excess return (in excess of the T-Bill rate) on aggregate financial wealth (i.e. the CAPM). Defining a factor model does not mean that we take a stand on the mechanism that transfer fundamentals into cross-sectional dependence. Of course, given its residual nature, any statements on systemic risk will be conditional on a correct specification of the factor model. Our methodology is rather general and can be easily applied to any linear factor pricing model. To mitigate the model selection bias we consider other popular sources of systematic risks such as size, value and shocks to macroeconomic factors. In particular we consider the three-factor model initially proposed by Fama and French (1993), and an implementation of the Merton (1973) intertemporal extension of the CAPM (I-CAPM) including shocks to aggregate dividend yield and both default- and term-spreads as state variables, in addition to aggregate wealth. Data are from the Center for Research in Security Prices (CRSP), the FredII database of the St. Louis Federal Reserve Bank and Kenneth French’s website. The data for the 1-month T-Bill are taken from Ibbotson Associates.

Our empirical findings show that high systemic risk characterized financial markets across the period 2001/2002 (i.e. dot.com bubble, 9/11 attacks, Financial scandals, Iraq war), the
great financial crisis of 2008/2009, and the recent major Eurozone sovereign turmoil. Few financial firms such as JP Morgan, Bank of America and Bank of New York Mellon turns out to play a key role for systemic risk measurement, as they heavily outweigh other firms within the economic network. This pattern holds also at the industry level, with industries classified according to the Global Industry Classification Standard (GICS) developed by MSCI. In fact, while the Energy sector is key within periods of low systemic risk, the financial sector plays a crucial role globally when the probability of contagion across firms is high. This evidence is in line with Barigozzi and Brownlees (2013) and Diebold and Yilmaz (2014). Interestingly, we show that exposures to sources of systematic risk also change across firms when systemic risk increases. For instance, exposure to both market and default risks tend to be higher in the financial sector when systemic risk increases.

Building on these results, we show that the centrality feature of the financial sector can not be reconciled with its relative market value. By using a Probit regression analysis we show that systemic risk can be significantly predicted by increasing credit and default yield spread, although such predictability power is low in magnitude. Also, we show that our model-implied systemic risk indicator significantly predicts aggregate financial distress measured through the St.Louis Fed Financial Stress Index. As such, our methodology can be thought of as an early warning indicator to regulators and the public.

The remainder of the paper proceeds as follows. Section 2 lays out the model. Section 3 shows results from a simulation example. Section 4 discuss the data, the prior elicitation and reports the main empirical results. The relationship between systemic risk, macroeconomic variables and financial distress is investigated in Section 5. Section 6 concludes. We leave to the Appendix derivations details and additional results.

2 Measuring Systemic Risk

We identify contagion as an increase in the strength of network connectedness. In general, any network can be described by a $p \times p$ adjacency matrix, $A$, consisting of $p$ unique “nodes” which are connected through “edges”. Each entry in the adjacency matrix $A$, denoted $a_{ij}$, for row $i$
and column \( j \), records the connection between nodes \( i \) and \( j \):

\[
[A]_{ij} = \begin{cases} 
  a_{ij} = 1 & \text{if } i \text{ and } j \text{ are connected} \\
  a_{ij} = 0 & \text{otherwise}
\end{cases}
\]  

(1)

Our approach to measure network connectedness grounds on Graph theory. Loosely speaking, a graph is a visual object defined by the pair \((V,E)\) where \(V\) is the vertex set of \(p\) elements (companies) and \(E\) defines the edge-set (the set of linkages among companies). In fact, adjacency matrix and graph are implicitly synonymous in most of the empirical applications. If \( G = (V,E) \) is an undirected graph and \( X \) a general multi-variate normal random variable, we can model the covariance structure \( \Sigma \), by considering its restrictions imposed the graph, or network, structure \( G \); namely, the covariance structure has off-diagonal zeros corresponding to conditional orthogonality among the elements of the vector of exogenous shocks.\(^4\)

The network structure is conditioned on the presence of sources of systematic risk. The undirected graphical representation of the economic network is inferred from the residuals of a linear asset pricing model. Defining a factor model does not mean that we take a stand on the mechanism that transfer fundamentals into cross-sectional dependence. Intuitively, given the residual nature of the network structure, any statements on contagion will be conditional on a correct specification of the factor model. In an attempt to mitigate a selection bias for systematic risk factors we considered some representative alternative factor model specification. In fact, our methodology is rather general and can be easily applied to any linear factor pricing model.

Given systematic risk factors do not change across stocks, we consider a seemingly unrelated regression model (SUR) as a data generating process. Let \( y_{it} \) represents the excess returns on the \( ith \) industry at time \( t \), and \( x_{it} \) the \( n_i \)-dimensional vector of common factors with possibly a

\(^4\)Graphical structuring of multivariate time series is often referred as to Gaussian graphical modeling (see Erdős and Rényi 1959, Dempster 1972, Dawid and Lauritzen 1993 and Guidici and Green 1999 for more details). Given the residual nature of systemic risk with respect to sources of systematic risk, we assume the graph is undirected, meaning there is no particular direction in the conditional dependence structure among firms. However, directed graphical models can be easily accomplished within our modeling framework and we leave that for future research. In the Gaussian set up, zeros in the precision matrix simply express conditional independence restrictions. It can be showed that the covariance structure belongs to \( M(G) \), the set of all positive-definite symmetric matrices with elements equal to zero for all \((i,j) \notin E\) (e.g. Carvalho and West 2007).
constant term for individual $i$ at time $t$; the model dynamics can be summarized as

$$y_t = X_t' \beta_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}_p \left(0, \Sigma_t(G_t)\right)$$

(2)

t = 1, \ldots, T$, where $y_t = (y_{1t}, \ldots, y_{pt})'$ is a $p$-dimensional vector of returns in excess of the risk-free rate, $X_t = \text{diag}\{(x_{1t}, \ldots, x_{pt})\}$ a $n \times p$ matrix of explanatory variables, with $n = \sum_{i=1}^{p} n_i$, $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{pt})'$ a $p$-vector of normal random errors. The dynamics described in (2) is fairly general since represents an approximation of a reduced-form stochastic discount factor where the risk factors are assumed to capture investors’ beliefs on the business cycle (see Liew and Vassalou 2000, Cochrane 2001, and Vassalou 2003).

The variance-covariance matrix $\Sigma_t$ is consistent with the restrictions implied by the underlying network structure (i.e. the graph) $G_t$, and thus reflects the level of firms connectedness at time $t$. Also, we assume that the vector of exposures to systematic risks $\beta_t = (\beta_{1t}, \ldots, \beta_{pt})'$, the covariance matrix $\Sigma_t$, and the network $G_t$ have a Markov regime-switching dynamics. They are driven by an unobservable state $s_t \in \{1, \ldots, K\}$, $t = 1, \ldots, T$, that takes a finite number $K$ of values and represents network system-wide connectedness, namely systemic risk. Such state $s_t$ evolves as a Markov chain process, where the transition probability $\pi_{ij}$, of going from the $i$th to the $j$th state in one step is time-invariant (see, e.g. Hamilton 1994), that is $P(s_t = i|s_{t-1} = j) = \pi_{ij}$, $i, j = 1, \ldots, K$, for all $t = 1, \ldots, T$.

The choice of a Markov regime-switching dynamics is motivated by the common definition of contagion as abrupt increase in the cross-sectional dependence structure of institutions/sectors/countries after a shock (e.g. Forbes and Rigobon 2000). Also, the Markov regime-switching nature of the covariance structure allows to acknowledge the heteroskedasticity bias highlighted in Forbes and Rigobon (2002).\footnote{Markov regime-switching models are very popular in the finance literature since Ang and Bekaert (2002), Guidolin and Timmermann (2007), and Guidolin and Timmermann (2008), as they allows for economic interpretation of the regimes and for a direct statistical identification of the time periods corresponding to different market phases.}

As typical in SUR models we assume that the exogenous shocks are possibly contemporaneously correlated, but not autocorrelated. The Markov-switching graphical model specification in equation (2) makes the exposures to
sources of systematic risk time varying and directly depending on the regime of systemic risk;

\[ \beta_t = \sum_{k=1}^{K} \beta_k I_{\{k\}}(s_t) \]  

(3)

with \( I_{\{k\}}(s_t) \) the indicator function which takes value one when the state \( s_t \) takes value \( k \) at time \( t \) and zero otherwise. The state-specific covariance matrix \( \Sigma_k \) is constrained by a state-specific graph \( G_k \), that is

\[ \Sigma_t = \sum_{k=1}^{K} \Sigma_k (G_k) I_{\{k\}}(s_t), \quad G_t = \sum_{k=1}^{K} G_k I_{\{k\}}(s_t) \]  

(4)

with \( \Sigma_k \in \mathcal{M}(G_k) \) and \( \mathcal{M}(G_k) \) the set of all positive-definite symmetric matrices with elements equal to zero for all \( (i,j) \notin E \), given the state \( s_t = k \). In the model, contagion is generated by both the number of edges in \( G_t \) when \( s_t = k \), and the magnitude of the dependence between nodes measured by the correlation. Traditional connectedness measures do not distinguish between these two sources and therefore may result in biased estimates. Also, the features of the state-specific graph \( G_k \) play a crucial role in the estimation of our regime-switching model, since they allow us to identify the regimes of low and high systemic risk exposure.

Different concentration measures have been proposed to characterize the network connectedness. In this paper, we assume that a connectivity measure \( q = h(G_k) \) is a map function \( h \) from the graph space \( \mathcal{G} \) to the set of the real numbers \( \mathbb{Q} \subset \mathbb{R} \). In particular, the identification of the network structure across regimes is made by using two alternative measures of centrality, namely degree and eigenvector centrality. Degree centrality is defined as the number of links connected to the company \( i \); it can be interpreted as the immediate risk of the \( ith \) firm to be hit by a shock flowing through the economy.\(^6\) At the firm level, degree centrality is defined as the number of edges of the corresponding sub-graph \( G_{v,k} \).

\[ d_{i,k} = 2 \sum_{j=1}^{n} a_{ij,k} - n \]  

(5)

with \( a_{ij,k} \) the \( ijth \) element of the adjacency matrix in the state \( s_t = k \), and \( n \) represents the

\(^6\) The graphical structure is undirected therefore we cannot distinguish between indegree and outdegree. Accordingly, indegree counts the number of links directed to the node and outdegree is the number of links that the node directs to others.
cardinality of the set of nodes, \( n = |V| \). The concept of degree centrality at the company level can be extended at the industry level by considering those firms within a certain sector. For instance, degree centrality of the financial sector can be computed as

\[
q_{\text{fin},k} = \frac{1}{n_{\text{fin}}} \sum_{i \in V_{\text{fin}}} d_{i,k} 
\]

with \( n_{\text{fin}} = |V_f| \), and \( V_f \) the set of nodes associated to firms classified as “financials” according to the GICS. Of course, degree centrality can be computed at the network level by averaging out the single degrees for each company;

\[
q_{\text{global},k} = \frac{1}{n} \sum_{i=1}^{n} d_{i,k}
\]

while \( d_{i,k} \in [0, n-1] \), the industry and the global degree centrality measures are bounded between zero and one; i.e. \( Q = [0,1] \). Although widely used in the network literature, average degree is of limited usefulness. Indeed, such measure gives a simple count of the number of connections a company has, without effectively discriminating the relative importance of these connections with respect to the whole economic system. In other words, degree centrality, in its simplified version, is based on the assumption that all connections are equally weighted, and therefore carry the same importance for the transmission mechanism of shocks from the single firm to the economic system. Intuitively, firms in large sectors such as “industrials” are likely highly connected to each other. This implies that the average degree of the industrial sector is high. However, this does not imply that a shock to, say, Fedex can quickly spread to the financial sector.

To overcome this issue we follow Billio et al. (2012) and propose the use of a more sophisticated measure of centrality; the so-called eigenvector centrality measure. Google’s PageRank is a variant of the Eigenvector centrality measure. Such measures allows to take into account that cross-firms connections are not all equal. More prominently, eigenvector centrality measures the actual influence of a company in the economic network by assigning relative scores to firms based on how connected they are to the rest of the network; for the \( i \)th firm eigenvector
centrality can be computed as

\[ x_{i,k} = \frac{1}{\lambda_k} \sum_{j \in N(i,k)} x_{j,k} \]

where \( N(i,k) \) the set of neighbors of \( i \) given the state \( s_t = k \), and \( \lambda_k \) is a constant. Equation (8) can be rewritten in a more compact form as

\[ A_k x_k = \lambda_k x_k, \quad \text{such that} \quad q_{E,k} = x_{j^*,k} \quad (9) \]

with \( A_k \) the adjacency matrix defined as in (1) for \( s_t = k \), \( x = (x_1, x_2, ..., x_p) \), and \( j^* = \arg \max \{ \lambda_j, j = 1, \ldots, n \} \) is the index corresponding to the greatest Laplacian eigenvalue, \( \lambda_j \), \( j = 1, \ldots, n \), are the Laplacian eigenvalues.\(^7\) For this measure \( Q = \mathbb{R} \). We can approximate the eigenvector centrality at the industry level by averaging \( x_{i,k} \) within a certain industry. For instance, the average eigenvector centrality for the financial sector can be approximated as

\[ x_{\text{fin},k} = \frac{1}{n_{\text{fin}}} \sum_{i \in V_{\text{fin}}} x_{i,k} \quad (10) \]

If the adjacency matrix has non-negative entries, a unique solution is guaranteed to exist by the Perron-Frobenius theorem. The eigenvector centrality gives to each company an importance within the economic system that depends both on the number and the quality of its connections with respect to other firms. The number of connections still counts, but an institution with a small number of relevant connections may outrank one with a large number of mediocre linkages.

### 2.1 Estimation and Inference on Networks and Parameters

Our estimation approach generalizes earlier literature and consider a joint inference scheme on networks and parameters in large dimensional setting, fully acknowledging the uncertain nature of both. Given the fairly relevant complexity and non-linearity of the model, we opted for a Bayesian estimation scheme of the network \( G_k \) and the structural parameters \( \theta_k = (\beta_k, \Sigma_k, \pi_k) \), with \( \pi_k \) the \( k \)th row of the transition matrix \( \Pi \) for the latent state, \( s_t = k \). Also, by using

\(^7\)The Laplacian eigenvalues are the eigenvalues arranged in nonincreasing order of the Laplacian matrix, \( L = D - A \), where \( D = \text{diag}\{d_1, \ldots, d_n\} \) is a diagonal matrix with the vertex degree on the main diagonal. Here, \( z_j, j = 1, \ldots, n \), are the corresponding Laplacian eigenvectors.
Bayesian tools we can generate posterior distributions of virtually any sufficient statistics for the underlying network, as well as for any of the structural parameters of the linear factor pricing model, something that earlier literature did not provide.

2.2 Prior Specification

For the Bayesian inference to work, we need to specify the prior distributions for the network and the structural parameters. For a given graph \( G_k \) and state \( s_t = k \) the prior structure is conjugate and the model dynamics (2) reduces to a standard SUR model (e.g., see Chib and Greenberg 1995). This makes Bayesian updating straightforward and numerically feasible. As far as the systemic risk state transition probabilities are concerned we choose a Dirichlet distribution:

\[
(\pi_{k1}, \ldots, \pi_{kK}) \sim \text{Dir}(\delta_{k1}, \ldots, \delta_{kL})
\] (11)

with \( \delta_{ki} \) the concentration parameter for \( \pi_{ki} \), and \( \Pi_k = (\pi_{k1}, \ldots, \pi_{kK}) \) the \( k \)th row of the transition matrix \( \Pi \). The role of the covariance structure \( \Sigma_k \) is one of the most important in the SUR model specification. The non-diagonal structure of the residual covariance matrix improves parameter estimation by exploiting shared features of the \( p \)-dimensional vector of excess returns. However, an increasing \( p \) makes both the estimation error and complexity unfeasible to be managed. In this context we take advantage of natural restrictions induced by graphical model structuring (Carvalho and West 2007, Carvalho, West, and Massam 2007, and Wang and West 2009).

The prior over the graph structure is defined as a Bernoulli distribution with parameter \( \psi \) on each edge inclusion probability as an initial sparse inducing prior. That is, a \( p \) node graph \( G_k = (V_k, E_k) \) with \( |E_k| \) edges has a prior probability

\[
p(G_k) \propto \prod_{ij} \psi^{e_{ij}} (1 - \psi)^{(1-e_{ij})}
= \psi^{|E_k|} (1 - \psi)^{T-|E_k|}
\] (12)

with \( e_{ij} = 1 \) if \((i, j) \in E_k\). This prior has its peak at \( T \psi \) hedges, with \( T = p(p-1)/2 \), for
an unrestricted $p$ node graph, providing a flexible way to directly control for the prior model complexity. A uniform prior alternative might be used. However, as pointed out in Jones, Carvalho, Dobra, Hans, Carter, and West (2005), a uniform prior over the space of all graphs is biased towards a graph with half of the total number of possible edges. As the number of possible graphs for a $p$ node structure is, for large $p$, the uniform prior gives priority to those models where the number of edges is quite large. To induce sparsity and hence obtain a parsimonious representation of the interdependence structure implied by a graph, we choose $\psi = 2/(p - 1)$ which would provide a prior mode at $p$ edges. Conditional on a specified graph $G_k$ and state $s_t = k$, the joint posterior $p(\Sigma_k, \beta_k | Y)$ has a conjugate prior structure;

$$\Sigma_k \sim \mathcal{HIW}_{G_k} (d_k, D_k) \quad (13)$$

with $d_k$ and $D_k$ respectively the degrees of freedom and the scale hyper parameters, and $\mathcal{HIW}$ representing the Hyper Inverse-Wishart distribution (see Dawid and Lauritzen 1993) for the structured covariance matrix $\Sigma_k$. The prior for the betas is independent on the covariance structure,

$$\beta_k \sim \mathcal{N}_p (m_k, M_k) \quad (14)$$

with $m_k$ and $M_k$ the location and scale hyper-parameters, respectively.\(^8\) The choice of the prior hyper-parameters is discussed in Section 4. We also discuss extensively the sensitivity of posteriors with respect to priors settings in a separate online appendix.

### 2.3 Posterior Approximation

In order to find a Bayesian estimation of the parameters, the graphs and the latent states we follow a data augmentation principle (see Tanner and Wong 1987) which relies on the complete likelihood function, that is the product of the data and state variable densities, given the parameters and the graphs. Let us denote with $z_{s,t} = (z_{s}, \ldots, z_{t})$, $s \leq t$, a collection of vectors $z_{u}$. The collections of graphs and parameters are defined as $G = (G_1, \ldots, G_k)$ and

---

\(^8\)Notice that the fact that priors for the covariance structure and the betas are independent does not mean they are sample independently in the Gibbs sampler. Indeed, in the sampling scheme they are sampled conditionally on each other iteratively, and therefore can be thought as coming from the same joint distribution asymptotically.
\[ \theta = (\theta_1, \ldots, \theta_K), \] respectively, where \( \theta_k = (\beta_k, \Sigma_k, \pi_k) \), \( k = 1, \ldots, K \), are the state-specific parameters. The completed data likelihood is

\[
p(y_{1:T}, s_{1:T} | \theta, G) = \prod_{k,l=1}^{K} \prod_{t=1}^{T} \left( \frac{1}{2} \left( y_t - X_t' \beta_t \right) \Sigma_t^{-1} \left( y_t - X_t' \beta_t \right) \right)^{n/2} \exp \left( -\frac{1}{2} \left| \Sigma_t \right| - n/2 \right)
\]

with \( N_{kl,t} = I_{\{k\}}(s_t-1)I_{\{l\}}(s_t) \). Combining the prior specifications (11)-(14) with the complete likelihood (15), we obtain the posterior density

\[
p(\theta, G, s_{1:T} | y_{1:T}) \propto p(y_{1:T}, s_{1:T} | \theta, G) p(\theta, G)
\]

Since the joint posterior distribution is not tractable the Bayesian estimator of the parameters and graphs cannot be obtained in analytical form, thus we approximate the posterior distribution and the Bayes estimator by simulation. The random draws from the joint posterior distributions are obtained through a Gibbs sampler algorithm (Geman and Geman 1984). We propose a collapsed multi-move Gibbs sampling algorithm (see e.g. Roberts and Sahu 1997 and Casella and Robert 2004), where the graph structure, the hidden states and the parameter are sampled in blocks. More specifically we combine forward filtering backward sampling (see Frühwirth-Schnatter 1994 and Carter and Kohn 1994 for more details) for the hidden states, an efficient sampling algorithm for the covariance structure (see Carvalho and West 2007, Carvalho et al. 2007 and Wang and West 2009), and multi-move MCMC search for graph sampling (see e.g. Giudici and Green 1999 and Jones et al. 2005). At each iteration the Gibbs sampler sequentially cycles through the following steps:

1. Draw \( s_{1:T} \) conditional on \( \theta, G \) and \( y_{1:T} \).
2. Draw \( \Sigma_k \) conditional on \( y_{1:T}, s_{1:T}, G_k \) and \( \beta_k \).
3. Draw \( G_k \) conditional on \( y_{1:T}, s_{1:T} \) and \( \beta_k \).
4. Draw \( \beta_k \) conditional on \( y_{1:T}, s_{1:T} \) and \( \Sigma_k \).
5. Draw \( \pi_k \) conditional on \( y_{1:T}, s_{1:T} \).

From step 2 to 3 the Gibbs sampler is collapsed as \( G_k \) is drawn without conditioning on \( \Sigma_k \) since they are conditionally independent. In fact, the graph \( G_k \) is sampled marginalizing over
the covariance structure $\Sigma_k$ (see Carvalho and West 2007, Carvalho et al. 2007 and Wang and West 2009). A detailed description of the Gibbs sampler is given in the Appendix.

Inference on Markov-switching models, requires dealing with the identification issue arising from the invariance of the likelihood function to permutations of the hidden state variables. Different solutions to this problem have been proposed in the literature (see Frühwirth-Schnatter 2006 for a review). In this paper, we contribute to this stream of literature providing a way to identify regimes through graphs. More specifically we suggest to identify the regimes by imposing the following constraints on the state-specific graphs. We consider the following identification constraints on the intercept: $q(G_1) < \ldots < q(G_K)$, where $q$ is the average eigenvector centrality. This constraint allows us to interpret the first regime as the one associated with the lowest systemic risk level and the last regime as the one associated with the highest risk. In context where the eigenvector centrality is not sufficient to achieve a characterization of the regimes, then a complexity measure (see, e.g. Newman 2003, Emmert-Streib and Dehemer 2012), which combines information from different network measures, can be employed. From a practical point of view, we find in our empirical applications that eigenvector centrality ordering works as well as degree centrality constraint for the regime identification.

2.4 Posterior Network Connectedness

Given the prior distribution assumption and the Graphical model defined above, it is possible to define a posterior distribution of the graph $p(G_k|y_{1:T})$ and to assess the statistical properties of the network measures by employing the distribution defined by the transform $q = h(G_k)$. We develop a Gibbs sampling to generate samples from the graph posterior distribution, which can be used to approximate also the connectedness measure distribution;

$$p_{\mathcal{J}}(q_k|y_{1:T}) = \frac{1}{\mathcal{J}} \sum_{j=1}^{\mathcal{J}} \delta_{q_k}^{i}(q_k)$$ (17)

where $q_k^i = h(G_k^{(j)})$ and $G_k^{(j)}$ is the $j$th sample from the graph posterior distribution for the state $s_t = k$, and $\mathcal{J}$ is the number of Gibbs iterations. Usually, once a graph is estimated the network measure is applied to this graph, thus all information about graph uncertainty are lost. In this paper we propose to account for the uncertainty associated with the graph $G_k$, and suggest the
following integrated measure and its MCMC approximation

\[
\int_{G_k} h(G_k)p(G_k|y_{1:T})dG_k \approx \int_{Q} q_k p_j(q_k|y_{1:T})dq_k
\]

which is the empirical average of the sequence of measures \(q^j_k\), \(j = 1, \ldots, J\), associated with the MCMC graph sequence. As a whole, from the Bayesian scheme we can make robust hypothesis testing on the network structure as we are able to approximate, at least numerically, the entire distribution of networks conditioning on the state of contagion.

3 Simulation Example

Thus far we have introduced a tool for systemic risk measurement and emphasized its relationship to conditional dependence properties in a large dimensional time series setting. Before putting this tool at work in a real financial markets context, we want to assess the reliability of the estimation method through a simulation example. Specifically, we first investigate the ability of our inference scheme to effectively capture network connectedness across states; then we compare our proposed methodology against a standard Markov regime-switching SUR model. The purpose of the these simulation exercise is to show the effectiveness and efficiency of our systemic risk measurement scheme. Simulation results are based on a burn-in period of 2,000 draws out of 10,000 simulations storing every other of them.

First we simulate a sample of \(T = 1000\) observations \(y_t\), for \(p = 20\) assets and considering a single factor \(x_t \sim i.i.d. N(0, 1)\). We assume the existence of two persistence states with \(\pi_{11} = 0.95\) and \(\pi_{22} = 0.95\). For simplicity we assume that the betas on the single factor are constant across assets and are different across states, \(\beta_i (s_t = 1) = 0.6\) and \(\beta_i (s_t = 2) = 1.2\). The residual covariance structure is also changes across regimes and is consistent with an underlying regime-specific graph-based network \(G_k \in \mathcal{G}\). Network connectedness is set to be more concentrated (i.e. higher aggregate eigenvector centrality) in state \(s_t = 2\), which then represents high systemic risk. To avoid any particular effect of prior elicitation we choose fairly vague priors with \(d_k = 3\) and \(D_k = 0.0001I_p\) for both states and \(\psi = 2/(p - 1)\) for both states. We do not assume a priori any clear difference in the network structure across states. Panel A of Figure 1 shows
the adjacency matrix that defines the true network against the estimated one for the contagion state;

[Insert Figure 1 about here]

The figure makes clear that the model has a fairly good performance in identifying network connectivity, namely, the adjacency matrix $A$. In fact, the estimated graphical structure is short of two edges out of the nineteen in the original network.\(^9\)

In the second simulation exercise we compare our model against a benchmark SUR without network in the residual covariance matrix. To compare the utility from our method with respect to the benchmark SUR, we compute the estimation risk for $\Sigma_k$ using Stein’s loss function

$$\text{Loss} \left( \hat{\Sigma}, \Sigma \right) = \text{tr} \left( \hat{\Sigma} \Sigma^{-1} \right) - \log |\hat{\Sigma} \Sigma^{-1}| - p$$  \hspace{1cm} (18)

with $\hat{\Sigma}$ and $\Sigma$ the estimated and true residuals covariance structure, respectively. We conduct the experiment for different sample sizes, $T = 50, 100, 200$, with $p = 20$ assets and considering a single factor $x_t \sim i.i.d.N(0,1)$. As above, we consider a persistence contagion state $s_t = 2$, with $\pi_{22} = 0.95$. Betas are constant across assets and are different across states.

Panel B of Figure 1 shows box plots of the risk associated by different estimators across different sample sizes. For the sake of exposition, we label our model as $M1$ and the classic SSUR specification as $M2$. The figure makes clear that by fully acknowledging the network structure underlying the idiosyncratic covariance structure $\Sigma$ offers large gain over a standard SUR model. Such gains, are particularly significant when the ratio between assets and the sample size $p/T$ increases. This is consistent with previous evidence on the efficiency of sparse covariance estimates (see e.g. Carvalho et al. 2007 and Wang and West 2009, among others).

\(^9\)Inference on the graphical structure is made using an add/delete Metropolis-Hastings-within-Gibbs algorithm as originally proposed in earlier literature such as George and McCulloch (1993), Madigan and York (1995), George and McCulloch (1997), Giudici and Green (1999), and Jones et al. (2005), among the others. More details on the asymptotic properties of the estimation scheme and the sensitivity to different prior specifications are discussed in a separate online Appendix.
4 Empirical Analysis

As empirical application we measure systemic risk for a large set of companies. Systemic risk is jointly considered with sources of systematic risk which are assumed to capture investors’ beliefs on the business cycle (see Liew and Vassalou 2000, Cochrane 2001, Vassalou 2003, and Campbell and Diebold 2009). In particular, while the exposure to sources of systematic risk (i.e. betas) depends on the state of systemic risk, the latter directly depends on the betas given its residual nature. As such, although conditionally independent, systematic and systemic risks are not mutually exclusive. Although our methodology is rather general and can be easily applied to any linear factor pricing model, we consider few popular sources of systematic risks such as size, value and shocks to macroeconomic factors. This is mainly due to data availability at the daily frequency.

4.1 Data and Factor Pricing Models

We focus on the 100 blue chip companies that compose the S&P100 Index. We consider those institutions with more than 15 years of historical data, and then left with 83 companies. Table 1 summarize the firms in our dataset and the corresponding industry classification according to the Global Industry Classification Standard (GICS), developed by MSCI. Returns are dollar-valued and computed daily in excess of the risk-free rate. The sample period is 05/10/1996-10/31/2014 (4821 observations for each company), for a total of more than 400,000 firm-day observations. Our emphasis on stock returns is motivated by the desire to incorporate the most current information in the network analysis; stocks returns reflect information more rapidly than non-trading-based measures such as accounting variables.

We analyze three representative asset pricing models starting from a conditional version of the simple CAPM. Such model implies a unique risk factor which is represented by the excess return (in excess of the 1-month T-Bill rate) on the aggregate value-weighted NYSE/AMEX/NASDAQ index, taken from the Center for Research in Security Prices (CRSP). The return on the 1-month
T-Bill rate is taken from Ibbotson Associates, while returns on the market portfolio are taken from the Kenneth French’s website. The CAPM performed well in initial tests (e.g. Fama and MacBeth 1973), but has performed poorly since.

The second model considered is the well-known three-factor model initially proposed in Fama and French (1993). This model includes two empirically motivated additional systematic risk factors. In addition to excess return on aggregate wealth as for the simple CAPM, the model consists of a second risk factor, $SMB$, which represents the return spread between portfolios of stocks with small and large market capitalization. The third risk factor, $HML$, represents the return difference between “value” and “growth” stocks, namely portfolios of stocks with high and low book-to-market ratios.

Next, we consider one macroeconomic-based model. The third model is an empirical implementation of the Merton (1973) intertemporal extension of the CAPM. Based on Campbell (1996), who argues that innovations in state variables that forecasts changes in investment opportunities should serve as risk factors, we use aggregate dividend yield and both default- and term-spreads as state variables, in addition to aggregate wealth. Default spread is computed as the difference between the yields of long-term corporate Baa bonds and long-term government bonds. The term spread is measured the difference between the yields of 10- and 1-year government bonds. Data on bonds and treasuries are taken from the FredII database of the Federal Reserve Bank of St.Louis. The data for the 1-month T-Bill are taken from Ibbotson Associates.

We adopt the approach of Campbell (1996) and compute the changes in risk factors as the innovations of a first order Vector Auto-Regressive (VAR(1)) process. To ensure that betas are fully conditional and changes in risk factors satisfy the zero-conditional mean assumption, $E_{t-1}X_t = 0$, the VAR uses only historical data up to period $t - 1$. Thus, for each collection of the CRSP aggregate value-weighted market portfolio and the candidate set of risk factors $h_t = (r_{m,t}, x_t')'$, we estimate $h_\tau = B_{0,t} + B_{1,t}h_{\tau-1} + e_{t,\tau}$ for $\tau = 1, ..., t$. Following Petkova (2006), the innovations $e_{t,\tau}$ are orthogonalized from the excess return on the aggregate wealth and scaled to have the same variance.
4.2 Prior Choices and Parameters Estimates

Realistic values for different prior distributions obviously depend on the problem at hand. For the transition mechanism of systemic risk the prior hyper-parameters of the Dirichlet distribution are taken such that a priori systemic risk is persistent. Such prior belief is mainly based on the common wisdom that increasing network connectedness is not a quickly mean-reverting process (see e.g. Forbes and Rigobon 2002).

Given the large dimensional setting of the model, training the priors with firm-specific information might be prohibitive. We take an agnostic perspective in setting the hyper-parameters of the betas across institutions. The prior location parameter $m_k = 0$ for each $k = 1, ..., K$. The corresponding prior scale is set equal to $M_k = 1000I_p$ across states. Notice we do not force posterior estimates in any direction across states as the prior structure does not differ across low vs high systemic risk states.

The prior degrees of freedom and scale of the Hyper-Inverse Wishart distribution for the conditional covariance matrix are set to be $d_k = 3$ and $D_k = 0.0001I_p$, respectively. This is also a fairly vague, albeit proper, prior distribution. Finally, the prior for the graph space is a Bernoulli distribution. We have chosen an hyper-parameter equal to $\psi = 2/(p−1)$ which would provide a prior mode at $p$ edges. We could alternatively use a uniform prior over the space of all graphs. However as pointed out in Jones et al. (2005), a uniform prior would be biased towards a graph with half of the total number of possible edges. For large $p$, the uniform prior gives priority to those models where the number of edges is quite large. In a separate online appendix we show that posterior results are not very sensitive to the prior settings for the hyper-parameters that govern the prior conditional betas and covariances.

In order to further reduce the sensitivity of posterior estimates to the prior specification, we use a burn-in sample of 2,000 draws storing every other of the draws from the residuals 10,000 draws (see e.g. Primiceri 2005). The resulting auto-correlations of the draws are very low. A convergence analysis in Section B of the online Appendix shows that this guarantees accurate inference in our network based linear factor model.

Figure 2 shows the probability of high systemic risk in the economy over the testing sample.
The gray area represents the model-implied probability, while the red line shows the NBER recession indicator for the period following the peak of the recession to through the through. The figure makes clear that a wide state of contagion characterizes the period 2001/2002 (i.e. dot.com bubble, 9/11 attacks, Financial scandals, Iraq war), the great financial crisis of 2008/2009, and the recent major Eurozone sovereign turmoil.

Although there is mis-matching with respect to the business cycle indicator across the period 1998-2002, the NBER recession and high systemic risk tend to overlap across the recent great financial crisis. The last period of high systemic risk can be linked to the European sovereign debt crisis. As we would expect such period does not coincide with any recession period in the United States.

Figure 3 shows the persistence parameters for systemic risk for each of the factor pricing model considered. The first three boxplot report the probability of staying in a state of low systemic risk. The last three boxplot show the persistence of high systemic risk in the economy.

Systemic risk persists with an average probability of \( \pi_{hh} = 0.93 \), implying that the duration of a period of high systemic risk is around \( \frac{1}{1 - \pi_{hh}} = 14 \) days, while the long run probability of high systemic risk is equal to \( \frac{1 - \pi_{ll}}{2 - 2 \pi_{hh} - \pi_{ll}} = 0.33 \). This means that, in our sample the economy tend to be affected by high systemic risk for about a third of trading days, unconditionally.

Figure 4 shows changes in exposures to sources of systematic risks from low to high systemic risk, computed from the Fama-French three-factor model. For the sake of exposition, results are labeled according to the GISC industry classification. Top left panel shows the difference in the intercepts across companies. The figure makes clear that the Jensen’s alphas do not change across different regimes of systemic risk in a significant way. Indeed, the zero line never falls outside the 95% confidence interval of the model estimates. Interestingly, the differences in exposures to the aggregate wealth risk factor is significantly negative for financial firms. This
implies that the exposure to market risk of financial firms increases when systemic risk is higher. The only exception within the financial sector is the Berkshire Hathaway Inc. of Warren Buffett.

Similarly, financial firms are more exposed to value risk when systemic risk is higher. Two exceptions are again Berkshire Hathaway Inc., together with Morgan Stanley. Also Citigroup, although has negative difference on the HML beta, it is not statistically significant. The Industrial and Materials sectors also show an increasing exposure to value premium when systemic risk is higher. Figure 5 shows changes to the conditional betas on shocks to macroeconomic risk factors in the I-CAPM implementation. As we would expect, the behavior of the betas on market risk is consistent with the Fama-French three-factor model. The only exception is again Berkshire Hathaway Inc., although the difference in the beta is negative, on average.

Interestingly, the Energy sector shows the opposite path with respect to Financials. In fact, the exposure to market risk of energy stocks tend to be lower when systemic risk is higher. Bottom left panel shows the change of exposures to default risk from low vs. high systemic risk. On average, exposure to default risk is higher when systemic risk is higher, although for a large fraction of the sample such negative delta is not statistically significant. In the financial sector, AIG, Morgan Stanley, Bank of America, and American Express tend to be more exposed to default risk when systemic risk increases. In the technology sector Microsoft, IBM, Intel and Oracle are more exposed to default risk during market turmoils. Bottom right panel shows that both Energy and Financials tend to be less exposed to the aggregate dividend yield when contagion is high.

4.3 Financial Networks

Thus far we have introduced tools to measure contagion and showed their efficiency and implications for systematic and systemic risk measurement. We now put those tools at work and investigate the evolution of networks connectedness over time. For the sake of completeness
we investigate network connectivity on the residuals covariance matrix under the CAPM, the three-factor Fama-French model and the I-CAPM implementation. The amount of systemic risk can be thought of as residual in nature with respect to sources of systematic risks, as it strongly depends on how much of systematic risk is captured by the model.

Figure 6 shows the connectivity of firms inferred from the residuals of the SUR CAPM. The size and the color of the nodes are proportional to their relevance in the network. More precisely, size and color reflect the eigenvector centrality of each node as computed from equation (8). A darker (bigger) blue color (node) means the corresponding firm is more systemically important for the economy.

[Insert Figure 6 about here]

Top panel shows the network when systemic risk is low. Figure 6 makes clear that Energy companies such as ConocoPhillips (COP), Apache (APA), Occidental Ptl. (OXY), and Exxon (XOM) are central for the economic system (dark blue nodes). Interestingly, few consumer companies such as Wal Mart (WMT), Costco (COST), Target (TGT), and Lowe’s Comp. (LOW) are tightly link to each other, although completely disconnected from the rest of the economy. The financial sector turns out to be relevant, although marginally less than the energy sector. Indeed, big financial firms such as JP Morgan (JPM), AIG, Bank of America (BAC) and Wells Fargo (WFC), although relevant, are not as central as, for instance, Exxon Mobile.

Bottom panel of Figure 6 shows that the situation changes when systemic risk is high. Financials now are key in the transmission mechanism of exogenous shocks with firms such as JP Morgan and Bank of America playing the major role. If we combine Figure 2 and Figure 6, we can intuitively confirm that in periods of market turmoils, the systemic importance of banks and the financial sector substantially increases. In other words, a shock to, for instance, Morgan Stanley, turns out to have a much bigger effect on the economy than an exogenous shock on, say, Wal Mart. The marginal importance of each firm on the economic system as a whole might be uniquely driven by their relative market size, or valuation. Figure 7 address this issue by showing the network connectivity measured from the three-factor Fama-French model residuals.

[Insert Figure 7 about here]
Top panel shows the network connectivity when systemic risk is low. Figure 7 confirms the key role of the Energy sector when cross-firm contagion is modest. Exxon Mobil, ConocoPhillips, Occidental Ptl., and Apache carry most of the systemic risk in the economic system. By controlling for size and value, the role of the financial sector when systemic risk is low decreases. Also, the economic network is now more sparse with lots of missing linkages. The energy and the financial sectors seem to create a sub-network themselves. Consistent with Figure 6, bottom panel of Figure 7 shows the key role of the financial sector in the network connectedness when systemic risk increases. Also, the figure makes clear that the highest portion of systemic risk is evidently carried on by the financial sector.

Finally, Figure 8 shows the network connectedness computed from the I-CAPM implementation including default and interest rate risks, in addition to aggregate wealth and dividend yield. Top panel shows connectivity when systemic risk is low. The results confirm what shown above. The Energy sector turns out to be most systemically important when the risk of contagion is low. Interestingly, by conditioning on macroeconomic risk factors, Health Care becomes more important. Johnson & Johnson (JNJ), Abbot Labs (ABT), Eli Lilly (LLY), and Merck & Company (MKR), are as important as Bank of America (BAC), AIG, JP Morgan (JPM) and Wells Fargo (WFC) in terms of individual contribution to aggregate systemic risk.

[Insert Figure 8 about here]

As shown in Figure 6, few consumer discretionary and staples companies such as Wal Mart (WMT), Costco (COST), Target (TGT), Lowe’s Comp. (LOW) and CVS are tightly link to each other, although completely disconnected from the rest of the economy. Similarly, Industrials such as 3M, United Tech (UTX), Boeing (BA), Honeywell Intl. (HON), Union Pacific (UNP), and Caterpillar (CAT) are disjoint from the rest of the economy once macroeconomic risks are considered, although highly connected to each other. Panel B shows the network connectedness when systemic risk is high. The systemic importance of Energy and Health Care sectors now decrease. Financials such as Bank of America (BAC), AIG, JP Morgan (JPM), Wells Fargo (WFC), Citigroup (C), and Bank of New York Mellon (BK) are now key for the transmission mechanism of individuals exogenous shocks to the whole economy. Consumer discretionary and
staples are now connected to the rest of the economy through Procter & Gamble (PG). As a whole, Figures 6-8, together with Figure 2 make clear that Financials are systemically important across market turmoils, as an exogenous shocks on these institutions can quickly and heavily affect the entire economic system.

4.3.1 Systemic Risk Across Companies. We now focus our attention to the contribution of single companies to systemic risk. Figure 9 shows the top 20 institutions ranked according to their median eigenvector centrality. The latter defines a measure of importance of the single node in the transmission mechanism of exogenous shocks from a single institution to the whole economic system. The median is computed across posterior simulations of the network structure as provided by equation (17). The red line (blue line) with circle (square) marks shows eigenvector centrality when systemic risk is low (high).

Panel A shows the results conditioning on aggregate financial wealth as a unique source of systematic risk (i.e. CAPM). Energy companies such as Exxon Mobile and Occidental Ptl. show the highest weight when systemic risk is low (red line, circle marks). However, since network connectedness is low as well, the corresponding centrality measures are low in magnitude albeit significant. Financial firms such as Bank of New York and JP Morgan rank 10th and 13th, respectively. The insurance sector giant AIG does not seem to be systemically important ranking 19th when systemic risk is low. As we would expect from Figures 6-8 Financials become more systemically important when network connectedness is higher. Now, JP Morgan and Bank of New York turns out to be highly important to the economic system. Also, AIG now ranks 6th and carries a large centrality feature for the economic network.

Panel B of Figure 9 makes the results stonger. Here eigenvector centrality of single institutions is computed conditioning on size and value measured by book-to-market ratio, in addition to aggregate wealth. Energy stocks such as Exxon Mobil carry a large weight when systemic risk is relatively low. When systemic risk is higher, Financials are crucial and carry a large fraction of systemic risk. In fact, Bank of America, for instance, is weighted the double of Exxon Mobil
and for times more than ConocoPhillips. Also, Panel B shows that network connectedness is much more concentrated around financial firms when we condition on size and value in addition to market risk. This is consistent with the idea that systemic risk (i.e. network connectedness) and systematic risks, although are not directly depending on each other, are not mutually exclusive. For instance, the average, median, eigenvector centrality under high systemic risk is around 0.017 with the three-factor Fama-French model, against the modest 0.009 obtained from the CAPM.

Bottom panel of Figure 9 shows median eigenvector centrality computed from the I-CAPM implementation with shocks to macroeconomic risk factors. Again, Energy companies such as Anadarko Ptl. (APC), ConocoPhillips (COP), Occidental Ptl. (OXY), Apache (APA), and Schlumberger (SLB) carry the highest weights when systemic risk is low. The magnitude of the median eigenvector centrality for other sectors is relatively low indicating a high concentration around the Energy, and possibly the Health Care, sectors. When systemic risk is higher (blue line), the weight of Financials tend to dominate other industries. Indeed, consistent with the CAPM and the three-factor Fama-French model, financial companies such as JP Morgan (JPM), Bank of America (BAC), Bank of New York Mellon (BK), AIG, Citigroup (C), and Wells Fargo (WFC) are highly systemically important.

Figure 9 also makes clear a separation between states of high vs low systemic risks. In fact, for instance for the three-factor model, the average eigenvector centrality of the top 20 institutions is 0.017 with high systemic risk, against an average median value of 0.0055 when contagion is low. Interestingly, the separation of network connectedness across systemic risk regimes is clearer once conditioning for macroeconomic risk (bottom panel).

We investigate the role of single companies for systemic risk by using also degree centrality as proposed in Section 2. Degree centrality gives a simple count of the number of connections a company has, without effectively discriminating the relative importance of these connections with respect to the economic network. In fact, in its simplified version, degree centrality is based on the assumption that all firms connections are equally weighted, and therefore carry the same importance for the transmission mechanism of exogenous shocks. Table 2 reports the top 10 companies ranked across median eigenvalue centrality and median degree. The median
is computed across posterior simulations of the network structure as provided by equation (17). Column 2, 3 and 4 parallel the results of figure 9. Degree centrality is also computed conditioning on different sources of systematic risks.

Panel A shows the top 10 institutions when systemic risk is low, and conditioning for aggregate wealth as the unique source of systematic risk. Columns 5, 6 and 7 report the median degree centrality. As far as the number of connections is concerned, different asset pricing models give different rankings of systemically important companies. Residuals from the CAPM indicates that Financials and Energy stocks are highly linked. Once we add size and value premia as additional sources of systematic risk factors, consumer discretionary and staples companies such as Home Depot (HD), Costco (COST), Lowe’s Comp. (LOW) and CVS ranks the highest. Finally, Johnson & Johnson (JNJ) (Health Care), shows the highest number of linkages once macroeconomic risks are considered.

These results show the limited usefulness of degree centrality as a measure of systemic risk as the ranking is highly dependent on the factor asset pricing model used. This contradicts columns 2,3, and 4 which reports the top 10 median eigenvector centralities. In fact, despite the sources of systematic risk considered, Energy sector always ranks as the most important for systemic risk measurement and management. Such contradiction is well understood in network analysis. Indeed, eigenvector centrality gives to each company an importance within the economic system that depends both on the number and the quality of its connections with respect to other firms. The number of connections still counts, but an institution with a small number of relevant connections may outrank one with a large number of mediocre linkages. This is the case of consumer discretionary and staples firms.

Panel B of Table 2 shows that, when network connectivity is high, degree and eigenvector centrality tend to converge. Financial companies such as JP Morgan, Bank of America, and Bank of New York Mellon consistently rank within the most connected companies, as far as the number of linkages is concerned. However, eigenvector centrality turns out to be more robust for systemic risk measurement as it is less dependent on the factor pricing model.
Finally column 8 shows the average market value of each institution across low and high systemic risk. The results makes evident that there is no clear cut one-to-one mapping between the relevance of the nodes and their market value. Except for Exxon Mobile, which ranks high across columns, General Electric (GE) and Microsoft (MSFT) have among the highest market valuations but do not appear in centrality measures.

4.3.2 Systemic Risk Across Industries. One might argue that despite the clear role of major financial companies such as JP Morgan, AIG and Bank of America, the financial sector might not necessarily be central as a whole. The answer is partly given by figures 6-8. These figures make clear the central role of the financial sector when systemic risk is high. For the sake of completeness we compute both eigenvector centrality and degree for each sector defined as in the GISC from MSCI. Degree and eigenvector measures are computed at the industry level as indicated in equation (6) and (10), respectively. Table 3 shows the ranking of industries according to posterior median eigenvector and degree centrality. Medians are computed across posterior simulations of the network structure as provided by equation (17).

[Insert Table 3 about here]

Panel A reports the results obtained considering aggregate wealth as the only source of systematic risk. Energy and financials are the sectors with the most important linkages with the economic network. Again, looking at the average market value across industries there is no clear-cut mapping with the corresponding connectivity ranking. When systemic risk is high (Panel B), results are even clearer. The financial industry shows the higher system-wide economic relevance, followed by the energy sector. Interestingly, last column shows that Telecomm services and Technology have the highest average market valuation although they rank at the bottom in terms of systemic risk relevance. Results are robust by including size, value and macroeconomic factors as additional sources of systematic risk. Figure 10 finally shows that, indeed, the disconnect between market value and systemic risk becomes clear by looking at the time series of the relative market value of each sector with respect to the rest of the economy.

[Insert Figure 10 about here]
Top left panel, for instance, represents the market value of the financial sector over the rest of the economy. The relative weight of the financial sector drops from 25% in 2006 to less than 10% across 2008. Figure 2 shows that across the crisis of 2008/2009 systemic risk is likely to be high, which implies indeed an opposite relationship between contagion and market value. The opposite is true for the Energy sector (top middle panel). In fact, the relative market value of the energy sector increases when systemic risk is high across the period 2008/2009. Same positive relationship might be drawn for Telecommunication Services as shown in the bottom right panel. Industrials and Materials do not show a clear directional relationship with systemic risk. Finally, the relative market value of the Tech industry spikes during late 90s and bounce back beginning of 2000. This is the well known dot.com bubble.

5 Systemic Risk, Financial Distress and the Business Cycle

At the outset of the paper we clarify that we do not take any stake in any particular underlying causal structure of an increasing network connectedness; rather, we take it as given and seek to measure systemic risk from an agnostic point of view. However, understanding systemic risk is of interest to understand financial crisis, and their relationship with the business cycle.

In this section we take a reduced form approach and investigate if variables which are arguably related with investors’ belief on the business cycle are related to our measure of systemic risk. Also, we investigate any early warning feature of our systemic risk indicator. We use several macro financial variables to capture business cycle effects and investors’ expectations on changes in the investment opportunity set. We consider the term-, default- and credit-yield spreads, the aggregate dividend yield and price-earnings ratio, the VIX index, the Market Uncertainty index proposed by Baker, Bloom, and Davis (2013), and the Financial Stress Index held by the Federal Reserve Bank of St. Louis.10

Figure 11 shows the time series of the macro-financial predictors and the model-implied

---

10Although these macro-financial variables can not be exactly linked to the real side of the economy, early literature showed that they can be sensibly assumed to capture investors’ beliefs on the business cycle as well as changes in the investment opportunity set (see Campbell 1996, Liew and Vassalou 2000, Cochrane 2001, and Vassalou 2003).
probability of high systemic risk.\textsuperscript{11}

Top middle panel shows the Financial Stress Index, which is computed on a weekly basis and greater than zero when the U.S. financial sector was in distress. The average value of the index is normalized to be zero. Thus, zero is viewed as representing normal financial market conditions. Values below zero suggest below-average financial market stress, while values above zero suggest above-average financial market stress. Interestingly, a value higher than zero coincide to the periods of high systemic risk according to our model. A similar relationship holds between systemic risk and the VIX index (top right panel). Spikes in market uncertainty captured by the VIX tend to be consistent with increasing systemic risk. Bottom left and right panels show that also default spread and aggregate dividend yield can be potentially correlated with systemic risk. For instance, an increasing default spread coincide with periods of high systemic risk. Finally, the term spread does not show any evident relationship with systemic risk.

Building on this visual results, we formally investigate and lagged or contemporaneous relationship between systemic risk and macro-financial variables. We estimate a Probit model considering different combinations of the above macro-financial predictors as the set of independent variables \( Z_t \). The dependent variable \( c_t \) is a systemic risk indicator takes value one if the probability of high systemic risk is higher than 0.5, and takes value zero otherwise. First, we consider the contemporaneous relationship between state variables and systemic risk; we estimate the model as

\[
    c_t = \gamma_0 + \gamma'_1 Z_t + \epsilon_t, \quad \epsilon_t \sim N (0, \tau^2)
\]  

(19)

Table 4 shows the estimates of the betas and the marginal effect of each independent variable.

\textsuperscript{11}Default spread is computed as the difference between the yields of long-term corporate Baa bonds and long-term government bonds. The term spread is measured the difference between the yields of 10- and 1-year government bonds. Credit spread is computed as the difference between the yields of long-term Baa corporate bonds and long-term Aaa corporate bonds. Data on bonds, treasuries and financial distress are taken from the FredII database of the Federal Reserve Bank of St.Louis. The data for the 1-month T-Bill are taken from Ibbotson Associates.
Panel A shows the estimated betas. Column 3 and 4 show evidence is in favor of a contemporaneous and positive relationship between systemic risk and credit and default spreads. Indeed, the marginal effect of default (credit) risk reported in Panel is 0.38 (0.87), meaning that a one unit increase in default (credit) risk implies an increasing probability of high systemic risk by one percent. However, while the pseudo $R^2$ by using default spread as unique predictor is 0.37, the same drops to 0.07 when using the credit risk premium as the only independent variable. The VIX index is also positive (beta is equal to 0.135) related to systemic risk and highly statistical significant (p-value is equal to 0.000). Interestingly, column 8 shows that there is a positive (beta equal to 1.842) contemporaneous relationship between systemic risk and financial distress. The corresponding pseudo $R^2$ is equal to 0.45.\footnote{Since the financial stress index is computed on a weekly basis, we transform the daily model-implied probability of high systemic risk to weekly. We obtain that by taking the probability computed on friday of each week or the last day of the week when friday is not an available trading day. This is consistent with the financial stress index which is indeed computed on friday of each week.}

Figure 11 shows that some of the independent variables such as aggregate dividend yield and default spread are not stationary. Using non-stationary variables as regressors in a Probit model may generate a spurious regression problem, namely the betas of table 4 are significant although there is no contemporaneous correlation in the data generating process between systemic risk and the business cycle. Also, equation (19) does not tell anything about the potential predictability of systemic risk. To investigate predictability of systemic risk and the non-stationarity of predictors we estimate a Probit regression model as follows;

$$c_t = \gamma_0 + \gamma'_1 \Delta Z_t + \epsilon_t, \quad \epsilon_t \sim N(0, \tau^2)$$  \hspace{1cm} (20)

using changes from time $t$ to $t-1$ as independent variables, $\Delta Z_t = Z_t - Z_{t-1}$. Intuitively, we want to investigate if an increase in, say, the credit yield spread is correlated with aggregate systemic risk. Table 5 reports the estimates of the betas and the marginal effect of each independent variable.

Interestingly, an increase in credit and default spreads is positively correlated with higher systemic risk, with a pseudo $R^2$ of 0.03 and 0.12, respectively. Other predictors such as aggregate dividend yield and price-earning ratio lose their significance. As such, an increase in dividend
yield does not lead to a higher systemic risk. Changes to aggregate financial distress are positively (0.424) and significantly (p-value= 0.001) correlated with systemic risk. Panel B shows that a one unit increase in the financial stress index raises by 0.26% the probability of high systemic risk. As a whole Table 5 shows that credit and default spreads have some predictability power for systemic risk. Also, changes in aggregate conditions of financial distress are positively correlated with systemic risk.

One important application of any systemic risk measure is to provide early warning signals to regulators and the public. To argue that our systemic risk measures can effectively be interpreted as early warning signal we have to investigate the predictability of financial distress on the basis of the model-implied systemic risk indicator $c_t$. We estimate a simple regression with the financial stress index of the St.Louis Fed and current plus lagged values of the model-implied high systemic risk indicator aggregated on a weekly basis. Panel A of Table 6 shows the results.

Column 2 (M1) confirms the positive and significant contemporaneous relationship between systemic risk and financial distress we found in Table 4. Column 3 (M3) shows that high systemic risk can predict a higher financial distress one week ahead. Indeed, the beta on lagged systemic risk is positive (1.331) and significant (p-value= 0.002), with and adjusted $R^2$ equal to 0.35. As shown in Figure 11 top middle panel the financial stress index is rather persistence. In order to mitigate any bias in the regression coefficient estimates we include lagged values of the dependent variable as regressors. By including the lagged dependent variable the magnitude of predictability sensibly decreases although remain significant.

For the sake of robustness we substitute the systemic risk indicator $c_t$ with the log of probability of systemic risk (LogProb). Panel B of Table 6 shows the results. The regression analysis mainly confirms the results of Panel A. Our systemic risk measure helps predict aggregate conditions of financial markets stress. Tables 4-6 lead us to conclude that changes in credit and default spreads can help predict systemic risk, and that such model-implied systemic risk may represents an early warning signal for aggregate financial markets stress conditions.
6 Conclusions

Contagion and systemic risk measurement have become overwhelmingly important over the last few years. After the great financial crisis the main question has been to what extent the economic system is robust to a shock to the financial sector. In the language of network analysis this boils down to ask what is the connectedness of financial firms with the rest of the economic network. We believe we contribute to answer this question by providing a useful and intuitive model for contagion and systemic risk (system-wide connectivity) measurement.

We take an asset pricing perspective and infer the network structure system-wide from the residuals of an otherwise standard linear factor pricing model. By conditioning on different sources of systematic risk we implicitly recognize that systematic and systemic risk might be independent but not mutually exclusive concepts. For the sake of completeness we consider different sources of systematic risks such as aggregate financial wealth, size, value and shocks to macroeconomic risk factors. For a given linear factor model, we measure contagion as a shift in the strength of the cross-firm network linkages. This is consistent with the common wisdom that posits contagion representing a significant increase in cross-sectional dependence across institutions/sectors/countries after a shock.

We estimate the model by developing a Markov Chain Monte Carlo (MCMC) scheme, which naturally embeds parameter uncertainty in the modeling framework. Unfortunately, parameter uncertainty is not a minor issue. Indeed, in a full information framework any inference on the economic network must be read as contingent on having full confidence in the parameters point estimates. However, this is rarely the case, especially in high dimensional time series settings. Moreover, alternative conceivable values of the parameters will typically lead to different networks. We address this situation by providing an exact finite-sample Bayesian estimation framework which helps generate posterior distribution of virtually any function of the linear factor model parameters/statistics.

An empirical application on daily returns of a large dimensional set of blue chip stocks, shows that financial firms and sector play indeed a crucial role in systemic risk measurement, beyond their relative market values. Interestingly, our model-implied systemic risk measures can
be interpreted as an early warning signal as helps to predicts in the very near future conditions of stress in financial markets.

By no means we argue that our model is a final result; but rather an initial step towards a more careful modeling of contagion and systemic risk. More generally, we see our paper as part of a vibrant emerging literature using network analysis in financial contexts, in which we have the merit of introducing time variation, system-wide inference, and parameter uncertainty in systemic risk measurement, which earlier literature did not provide.
References


Appendix

A The Gibbs Sampler

A.1 Sampling $s_{1:T}$

In order to draw the unobservable state at each time and iteration we use a forward filtering backward sampling (FFBS) algorithm (see Frühwirth-Schnatter (1994) and Carter and Kohn (1994)). As the state $s_t$ is discrete valued the FFBS is applied in its Hamilton form. The Hamilton filter iterates in two steps, namely prediction and updating. The prediction step at each time $t$ is

$$p(s_{t+1} = j|\theta, y_{1:t}) = \sum_{k=1}^{K} p_{kj} p(s_t = k|\theta, y_{1:t})$$  \hspace{1cm} (A.21)

The updating step can be easily derived as

$$p(s_{t+1} = j|\theta, y_{1:t+1}) = \frac{p(y_{t+1}|s_{t+1} = j, \theta, y_{1:t}) p(s_{t+1} = j|\theta, y_{1:t})}{p(y_{t+1}|y_{1:t}, \theta)}$$  \hspace{1cm} (A.22)

where the normalizing constant is the marginal predictive likelihood defined as

$$p(y_{t+1}|y_{1:t}, \theta) = \sum_{k=1}^{K} p(y_{t+1}|s_{t+1} = k, \theta, y_{1:t}) p(s_{t+1} = k|\theta, y_{1:t})$$  \hspace{1cm} (A.23)

The draw $p(s_{1:T}|y_{1:T}, \theta)$ can then be obtained recursively and backward in time by using the smoothed probabilities as

$$p(s_{1:T}|y_{1:T}, \theta) = p(s_T|y_{1:T}, \theta) \times \prod_{t=1}^{T-1} p(s_t|s_{t+1}, y_{1:T}, \theta)$$  \hspace{1cm} (A.24)

where for instance

$$p(s_t = k|s_{t+1} = j, y_{1:t}, \theta) = \frac{p_{kj} p(s_t = k|y_{1:t}, \theta)}{p(s_{t+1} = j|\theta, y_{1:t})}$$ \hspace{1cm} (A.25)

A.2 Sampling $\beta_k$ and $\Sigma_k$

Graphical structuring of multivariate normal distributions is often referred to covariance selection modelling (Dempster 1972). In working with covariance selection models, Dawid and Lauritzen (1993) defined a family of Markov probability distributions suitable for covariance matrices on decomposable graphs called Hyper-Inverse Wishart. From a Bayesian perspective, for each state $s_t = k$ and graphical structure $G_k$ the hyper-inverse Wishart turns out to be conjugate locally. Therefore, let $T_k = \{t : s_t = k\}$ and $T_k = Card(T_k)$, then the posterior for $\Sigma_k$ is

$$(\Sigma_k|y_{1:T}, \theta, s_{1:T}, \beta_k) \sim HIW_{G_k}(d_k + T_k, D_k + \sum_{t \in T_k} e_{tk}e_{tk}')$$  \hspace{1cm} (A.26)

where $e_{tk} = y_t - X_t'\beta_k$. Conditional on $s_{1:T}$ and $\Sigma_k$, the posterior for the regime-dependent betas $\beta_k$ is

$$(\beta_k|\Sigma_k, y_{1:T}, s_{1:T}) \sim N_0\left(M_k^+ \left(\sum_{t \in T_k} X_t \Omega_k y_t + M_k^{-1} m_k\right), M_k^+\right)$$  \hspace{1cm} (A.27)
with \( M_k^* = \left( \sum_{t \in T_k} X_t \Omega_k X_t' + M_k^{-1} \right)^{-1} \). Simulations from the hyper-inverse Wishart distribution is based on Carvalho et al. (2007).

**A.3 Sampling the Transition Matrix**

As regards the transition probabilities \( \pi_k = (\pi_{k1}, \ldots, \pi_{kK}) \), for the state \( s_t = k \), the conjugate Dirichlet prior distribution (11) updates as

\[
(\pi_{k1}, \ldots, \pi_{kK}|y_{1:T}, s_{1:T}) \sim \text{Dir}(\delta_{k1} + N_{k1}, \ldots, \delta_{kK} + N_{kK}) \tag{A.28}
\]

with \( N_{kl} = \sum_{t=1}^T I\{k\}(s_t) I\{l\}(s_{t-1}) \) the empirical transition probabilities between the kth and the lth state.

**A.4 Direct Graph Search within the Gibbs Algorithm**

In order to learn the Graph structure \( G_k \) conditional on the state \( k \) we apply a Markov chain Monte Carlo for multivariate graphical models (see, e.g. Giudici and Green 1999 and Jones et al. 2005). This relies on the computation of the unnormalized posterior over graphs \( p_k(G_k|y_{1:T}, s_{1:T}) \propto p(y_{1:T}, s_{1:T}|G_k)p(G_k) \), for any specified state \( k \). It is easy to check that due to the prior independence assumption of the parameters across regimes,

\[
p_k(y_{1:T}, s_{1:T}|G_k) = \int \int \prod_{t \in T_k} (2\pi)^{-n/2} |\Sigma_k|^{-n/2} \exp \left( \frac{1}{2} (y_t - X_t'\beta_k)' \Sigma_k^{-1} (y_t - X_t'\beta_k) \right) p(\beta_k)p(\Sigma|G_k) d\beta_k d\Sigma
\]

(A.29)

This integral cannot be evaluated analytically. We apply a Candidate’s formula along the line of Chib (1995) and Wang (2010). Such an approximation gives the value of the marginal likelihood via the identity \( p_k(y_{1:T}, s_{1:T}|G_k) = p_k(y_{1:T}, s_{1:T}, G_k, \beta_k, \Sigma_k)/p(\Sigma_k, \beta_k|y_{1:T}, s_{1:T}) \). As pointed out in Wang (2010), two different approximations may be viable by integrating over disjoint subsets of parameters (see the Appendix).

Following Jones et al. (2005) we apply a local-move Metropolis-Hastings based on the conditional posterior \( p_k(G|y_{1:T}, s_{1:T}) \). A candidate \( G' \) is sampled from a proposal distribution \( q(G'|G) \) and accepted with probability

\[
\alpha = \min \left\{ 1, \frac{p_k(G'|y_{1:T}, s_{1:T})q(G|G')}{p_k(G|y_{1:T}, s_{1:T})q(G'|G)} \right\} = \min \left\{ 1, \frac{p_k(G'|y_{1:T}, s_{1:T})p(G')q(G|G')}{p_k(G|y_{1:T}, s_{1:T})p(G)q(G'|G)} \right\}
\]

This add/delete edge move proposal is accurate despite entails a substantial computational burden.
Table 1. Company List

This table summarizes the companies in our dataset and the corresponding industry classification according to the Global Industry Classification Standard (GICS), developed by MSCI. These companies represent the subset of the blue chip stocks that constitute the S&P100 for which we have at least 15 years of daily data. The S&P100 composition listing is taken as of December 2014.

<table>
<thead>
<tr>
<th>ID</th>
<th>Ticker</th>
<th>Company Name</th>
<th>GICS Sector</th>
<th>ID</th>
<th>Ticker</th>
<th>Company Name</th>
<th>GICS Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MMM</td>
<td>3M</td>
<td>Industrials</td>
<td>42</td>
<td>HAL</td>
<td>Halliburton</td>
<td>Energy</td>
</tr>
<tr>
<td>2</td>
<td>T</td>
<td>AT&amp;T</td>
<td>Tel. Services</td>
<td>43</td>
<td>HPQ</td>
<td>Hewlett-Packard</td>
<td>Technology</td>
</tr>
<tr>
<td>3</td>
<td>ABT</td>
<td>Abbot Labs</td>
<td>Health Care</td>
<td>44</td>
<td>HD</td>
<td>Home Depot</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>4</td>
<td>ALL</td>
<td>All State</td>
<td>Financials</td>
<td>45</td>
<td>HON</td>
<td>Honeywell Intl</td>
<td>Industrials</td>
</tr>
<tr>
<td>5</td>
<td>MO</td>
<td>Altria Group</td>
<td>Cons. Stap.</td>
<td>46</td>
<td>INTC</td>
<td>Intel</td>
<td>Technology</td>
</tr>
<tr>
<td>6</td>
<td>AXP</td>
<td>American Exp</td>
<td>Financials</td>
<td>47</td>
<td>IBM</td>
<td>International Bus Mchs</td>
<td>Technology</td>
</tr>
<tr>
<td>7</td>
<td>AIG</td>
<td>American Intl Gp</td>
<td>Financials</td>
<td>48</td>
<td>JPM</td>
<td>JP Morgan Chase</td>
<td>Financials</td>
</tr>
<tr>
<td>8</td>
<td>AMGN</td>
<td>Amgen</td>
<td>Health Care</td>
<td>49</td>
<td>JNJ</td>
<td>Johnson &amp; Johnson</td>
<td>Health Care</td>
</tr>
<tr>
<td>9</td>
<td>APC</td>
<td>Anadarko Petroleum</td>
<td>Energy</td>
<td>50</td>
<td>LLY</td>
<td>Eli Lilly</td>
<td>Health Care</td>
</tr>
<tr>
<td>10</td>
<td>APA</td>
<td>Apache</td>
<td>Energy</td>
<td>51</td>
<td>LMT</td>
<td>Lockheed Martin</td>
<td>Industrials</td>
</tr>
<tr>
<td>11</td>
<td>AAPL</td>
<td>Apple</td>
<td>Technology</td>
<td>52</td>
<td>LOW</td>
<td>Lowe’s Comp.</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>12</td>
<td>BAC</td>
<td>Bank of America</td>
<td>Financials</td>
<td>53</td>
<td>MCD</td>
<td>McDonald’s</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>13</td>
<td>BAX</td>
<td>Baxter Intl</td>
<td>Health Care</td>
<td>54</td>
<td>MDT</td>
<td>Medtronic</td>
<td>Health Care</td>
</tr>
<tr>
<td>14</td>
<td>BRKB</td>
<td>Berkshire Hathaway</td>
<td>Financials</td>
<td>55</td>
<td>MKR</td>
<td>Merck &amp; Company</td>
<td>Health Care</td>
</tr>
<tr>
<td>15</td>
<td>BHB</td>
<td>Biogen Idec</td>
<td>Health Care</td>
<td>56</td>
<td>MSFT</td>
<td>Microsoft</td>
<td>Technology</td>
</tr>
<tr>
<td>16</td>
<td>BA</td>
<td>Boeing</td>
<td>Industrials</td>
<td>57</td>
<td>MS</td>
<td>Morgan Stanley</td>
<td>Financials</td>
</tr>
<tr>
<td>17</td>
<td>BMY</td>
<td>Bristol Myers Squibb</td>
<td>Health Care</td>
<td>58</td>
<td>NKE</td>
<td>Nike</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>18</td>
<td>CVS</td>
<td>CVS Health</td>
<td>Cons. Stap.</td>
<td>59</td>
<td>NSC</td>
<td>Norfolk Southern</td>
<td>Industrials</td>
</tr>
<tr>
<td>19</td>
<td>COF</td>
<td>Capital One Finl.</td>
<td>Financials</td>
<td>60</td>
<td>OXY</td>
<td>Occidental Plt.</td>
<td>Energy</td>
</tr>
<tr>
<td>20</td>
<td>CAT</td>
<td>Caterpillar</td>
<td>Industrials</td>
<td>61</td>
<td>ORCL</td>
<td>Oracle</td>
<td>Technology</td>
</tr>
<tr>
<td>21</td>
<td>CVX</td>
<td>Chevron</td>
<td>Energy</td>
<td>62</td>
<td>PEP</td>
<td>PepsiCo</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>22</td>
<td>CSCO</td>
<td>Cisco System</td>
<td>Technology</td>
<td>63</td>
<td>PFE</td>
<td>Pfizer</td>
<td>Health Care</td>
</tr>
<tr>
<td>23</td>
<td>C</td>
<td>Citigroup</td>
<td>Financials</td>
<td>64</td>
<td>PG</td>
<td>Procter &amp; Gamble</td>
<td>Cons. Stap.</td>
</tr>
<tr>
<td>24</td>
<td>KO</td>
<td>Coca Cola</td>
<td>Cons. Stap.</td>
<td>65</td>
<td>QCOM</td>
<td>Qualcomm</td>
<td>Technology</td>
</tr>
<tr>
<td>25</td>
<td>CL</td>
<td>Colgate-Palm.</td>
<td>Cons. Stap.</td>
<td>66</td>
<td>RTN</td>
<td>Raytheon</td>
<td>Industrials</td>
</tr>
<tr>
<td>26</td>
<td>CMCSA</td>
<td>Comcast</td>
<td>Cons. Disc.</td>
<td>67</td>
<td>SLB</td>
<td>Schlumberger</td>
<td>Energy</td>
</tr>
<tr>
<td>27</td>
<td>COP</td>
<td>ConocoPhillips</td>
<td>Energy</td>
<td>68</td>
<td>SPG</td>
<td>Simon Property Grp.</td>
<td>Financials</td>
</tr>
<tr>
<td>28</td>
<td>COST</td>
<td>Costco</td>
<td>Cons. Stap.</td>
<td>69</td>
<td>SO</td>
<td>Southern</td>
<td>Utilities</td>
</tr>
<tr>
<td>29</td>
<td>DVN</td>
<td>Devon Energy</td>
<td>Energy</td>
<td>70</td>
<td>SBUX</td>
<td>Starbucks</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>30</td>
<td>DOW</td>
<td>Dow Chemical</td>
<td>Materials</td>
<td>71</td>
<td>TGT</td>
<td>Target</td>
<td>Cons. Disc</td>
</tr>
<tr>
<td>31</td>
<td>DD</td>
<td>DuPont</td>
<td>Materials</td>
<td>72</td>
<td>TXN</td>
<td>Texas Instruments</td>
<td>Technology</td>
</tr>
<tr>
<td>32</td>
<td>EMC</td>
<td>EMC</td>
<td>Technology</td>
<td>73</td>
<td>BK</td>
<td>Bank of New York Mellon</td>
<td>Financials</td>
</tr>
<tr>
<td>34</td>
<td>EXC</td>
<td>Exelon</td>
<td>Utilities</td>
<td>75</td>
<td>USB</td>
<td>US Bancorp</td>
<td>Financials</td>
</tr>
<tr>
<td>35</td>
<td>XOM</td>
<td>Exxon Mobil</td>
<td>Energy</td>
<td>76</td>
<td>UNP</td>
<td>Union Pacific</td>
<td>Industrials</td>
</tr>
<tr>
<td>36</td>
<td>FDX</td>
<td>Fedex</td>
<td>Industrials</td>
<td>77</td>
<td>UTX</td>
<td>United Tech</td>
<td>Industrials</td>
</tr>
<tr>
<td>37</td>
<td>F</td>
<td>Ford Motor</td>
<td>Cons. Disc.</td>
<td>78</td>
<td>UNI</td>
<td>UnitedHealth Grp.</td>
<td>Health Care</td>
</tr>
<tr>
<td>38</td>
<td>FCX</td>
<td>Freeport-McMoran</td>
<td>Materials</td>
<td>79</td>
<td>VZ</td>
<td>Verizon</td>
<td>Tel. Services</td>
</tr>
<tr>
<td>39</td>
<td>GD</td>
<td>General Dynamics</td>
<td>Industrials</td>
<td>80</td>
<td>WMT</td>
<td>WalMart</td>
<td>Cons. Stap.</td>
</tr>
<tr>
<td>40</td>
<td>GE</td>
<td>General Electric</td>
<td>Industrials</td>
<td>81</td>
<td>WAG</td>
<td>Walgreen</td>
<td>Cons. Stap.</td>
</tr>
<tr>
<td>41</td>
<td>GILD</td>
<td>Gilead Sciences</td>
<td>Health Care</td>
<td>82</td>
<td>DIS</td>
<td>Walt Disney</td>
<td>Cons. Disc.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>83</td>
<td>WFC</td>
<td>Wells Fargo</td>
<td>Financials</td>
</tr>
</tbody>
</table>

38
Table 2. Systemic Risk Measurement Across Companies

Systemic risk across companies. This table reports the top ten companies sorted by eigenvector centrality, degree centrality and market value. Eigenvector centrality measures the systemical importance of each company within the economic network. Degree centrality gives a simple count of the number of connections a company has. Market value is measured in million of dollars. The sample period is 05/10/1996-10/31/2014, daily. The network structure is computed conditioning on aggregate wealth (CAPM), then adding size and value risk factors (Fama-French), and conditioning on shocks to macro-finance state variables (I-CAPM).

Panel A: Low Systemic Risk

<table>
<thead>
<tr>
<th>Ranking</th>
<th>Eigenvector Centrality</th>
<th>Degree Centrality</th>
<th>Market Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CAPM</td>
<td>I-CAPM</td>
<td>Fama-French</td>
</tr>
<tr>
<td>1</td>
<td>Occidental Plt.</td>
<td>Anadarko Ptl.</td>
<td>Exxon Mobil</td>
</tr>
<tr>
<td>2</td>
<td>Exxon</td>
<td>ConocoPhillips</td>
<td>Schlumberger</td>
</tr>
<tr>
<td>3</td>
<td>Schlumberger</td>
<td>Bank of America</td>
<td>Shcumblerger</td>
</tr>
<tr>
<td>4</td>
<td>ConocoPhillips</td>
<td>Occidental Ptl.</td>
<td>Apache</td>
</tr>
<tr>
<td>5</td>
<td>Apache</td>
<td>Occidental Ptl.</td>
<td>Intel</td>
</tr>
<tr>
<td>6</td>
<td>Chevron</td>
<td>Johnson &amp; Johnson</td>
<td>ConocoPhillips</td>
</tr>
<tr>
<td>7</td>
<td>Bank of America</td>
<td>Eli Lilly</td>
<td>Halliburton</td>
</tr>
<tr>
<td>8</td>
<td>Halliburton</td>
<td>Abbot Labs</td>
<td>US Bancorp</td>
</tr>
<tr>
<td>9</td>
<td>US Bancorp</td>
<td>Wells Fargo</td>
<td>Wells Fargo</td>
</tr>
<tr>
<td>10</td>
<td>Bank of New York</td>
<td>JP Morgan Chase</td>
<td>American Exp</td>
</tr>
</tbody>
</table>

Panel B: High Systemic Risk

<table>
<thead>
<tr>
<th>Ranking</th>
<th>Eigenvector Centrality</th>
<th>Degree Centrality</th>
<th>Market Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CAPM</td>
<td>I-CAPM</td>
<td>Fama-French</td>
</tr>
<tr>
<td>1</td>
<td>JP Morgan Chase</td>
<td>JP Morgan Chase</td>
<td>Bank of America</td>
</tr>
<tr>
<td>3</td>
<td>Bank of America</td>
<td>Bank of New York</td>
<td>JP Morgan Chase</td>
</tr>
<tr>
<td>4</td>
<td>Wells Fargo</td>
<td>AIG</td>
<td>Wells Fargo</td>
</tr>
<tr>
<td>5</td>
<td>Citigroup</td>
<td>Citigroup</td>
<td>Exxon Mobil</td>
</tr>
<tr>
<td>6</td>
<td>AIG</td>
<td>Wells Fargo</td>
<td>US Bancorp</td>
</tr>
<tr>
<td>7</td>
<td>US Bancorp</td>
<td>Chevron</td>
<td>Citigroup</td>
</tr>
<tr>
<td>8</td>
<td>American Exp</td>
<td>Capital One Finl.</td>
<td>AIG</td>
</tr>
<tr>
<td>9</td>
<td>All State</td>
<td>All State</td>
<td>ConocoPhillips</td>
</tr>
<tr>
<td>10</td>
<td>Occidental Ptl.</td>
<td>Exxon Mobil</td>
<td>Chevron</td>
</tr>
</tbody>
</table>
Table 3. Systemic Risk Measurement Across Industries

Systemic risk across industries. This table reports the industries sorted by eigenvector centrality, degree centrality, and market value. Eigenvector centrality measures the systemical importance of each industry within the economic network. Degree centrality gives a simple count of the number of connections an industry has. Market value is measured in million of dollars and averaged across firms within the industry. Industry classification is based on the Global Industry Classification Standard (GICS) developed by MSCI. The sample period is 05/10/1996-10/31/2014, daily. The network structure is computed conditioning on aggregate wealth (CAPM), then adding size and value risk factors (Fama-French), and conditioning on shocks to macro-finance state variables (I-CAPM).

### Panel A: Low Systemic Risk

<table>
<thead>
<tr>
<th>Ranking</th>
<th>Eigenvector Centrality</th>
<th>Degree Centrality</th>
<th>Market Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CAPM</td>
<td>I-CAPM</td>
<td>CAPM</td>
</tr>
<tr>
<td>1</td>
<td>Energy</td>
<td>Energy</td>
<td>Energy</td>
</tr>
<tr>
<td>2</td>
<td>Financials</td>
<td>Financials</td>
<td>Materials</td>
</tr>
<tr>
<td>3</td>
<td>Materials</td>
<td>Health Care</td>
<td>Utilities</td>
</tr>
<tr>
<td>4</td>
<td>Utilities</td>
<td>Cons. Stap.</td>
<td>Health Care</td>
</tr>
<tr>
<td>6</td>
<td>Technology</td>
<td>Industrials</td>
<td>Technology</td>
</tr>
<tr>
<td>7</td>
<td>Cons. Stap.</td>
<td>Technology</td>
<td>Industrials</td>
</tr>
<tr>
<td>8</td>
<td>Health Care</td>
<td>Materials</td>
<td>Cons. Disc.</td>
</tr>
<tr>
<td>10</td>
<td>Tel. Services</td>
<td>Tel. Services</td>
<td>Tel. Services</td>
</tr>
</tbody>
</table>

### Panel B: High Systemic Risk

<table>
<thead>
<tr>
<th>Ranking</th>
<th>Eigenvector Centrality</th>
<th>Degree Centrality</th>
<th>Market Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CAPM</td>
<td>I-CAPM</td>
<td>CAPM</td>
</tr>
<tr>
<td>1</td>
<td>Financials</td>
<td>Financials</td>
<td>Financials</td>
</tr>
<tr>
<td>2</td>
<td>Materials</td>
<td>Energy</td>
<td>Materials</td>
</tr>
<tr>
<td>6</td>
<td>Cons. Stap.</td>
<td>Technology</td>
<td>Materials</td>
</tr>
<tr>
<td>7</td>
<td>Health Care</td>
<td>Cons. Stap.</td>
<td>Industrials</td>
</tr>
<tr>
<td>8</td>
<td>Technology</td>
<td>Industrials</td>
<td>Cons. Disc.</td>
</tr>
<tr>
<td>10</td>
<td>Cons. Disc.</td>
<td>Tel. Services</td>
<td>Tel. Services</td>
</tr>
</tbody>
</table>
Table 4. Systemic Risk and Financial Variables

Systemic risk and standard predictors. This table report the results from a Probit regression analysis where the dependent variable is the model implied systemic risk indicator $c_t$. The set of independent variables are the term yield spread (TERM, the difference between the 10-year interest rate and the 1-month T-Bill rate), the default spread (DEF, the difference between the 30-year treasury yield and the yield on a Baa corporate bond), the aggregate market dividend yield (DY), the credit spread (Credit, the difference between the Baa and the Aaa corporate bond yields), the financial distress index (Distress, a synthetic indicator of financial distress in the U.S.), the aggregate price-earnings ratio (PE), the market uncertainty index (Mkt Unc) from Baker et al. (2014), and the VIX index. Data are from the FredII database of the St Louis Fed and the Chicago Board Options Exchange (CBOE). The sample period is 05/10/1996-10/31/2014, daily. Panel A shows the estimated betas and Panel B the marginal effects. *** means statistical significance at the 1% confidence level, ** significance at the 5% confidence level and * significance at the 10% level.

<table>
<thead>
<tr>
<th>Panel A: Betas</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
<th>M9</th>
<th>M10</th>
<th>M11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.017</td>
<td>-1.336***</td>
<td>-4.625***</td>
<td>0.895***</td>
<td>-2.382***</td>
<td>-3.261***</td>
<td>-0.407***</td>
<td>-0.566***</td>
<td>-0.331</td>
<td>-7.691***</td>
<td>-3.301***</td>
</tr>
<tr>
<td>Term</td>
<td>-0.185***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit</td>
<td>1.001***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Default</td>
<td>2.278***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DY</td>
<td>-0.685***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td></td>
<td>0.101***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td></td>
<td></td>
<td>0.135***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distress</td>
<td></td>
<td></td>
<td></td>
<td>1.842***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt Unc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.004***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.03</td>
<td>0.07</td>
<td>0.37</td>
<td>0.04</td>
<td>0.11</td>
<td>0.29</td>
<td>0.45</td>
<td>0.05</td>
<td>0.56</td>
<td>0.59</td>
<td>0.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Marginal Effects</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
<th>M9</th>
<th>M10</th>
<th>M11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term</td>
<td>-0.071</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit</td>
<td>0.381</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Default</td>
<td>0.875</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DY</td>
<td>-0.257</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td>0.038</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td>0.051</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distress</td>
<td>0.671</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt Unc</td>
<td>0.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

It
Table 5. Systemic Risk and Changes in Financial Variables

Systemic risk and standard predictors. This table reports the results from a Probit regression analysis where the dependent variable is the model implied systemic risk indicator $c_t$. The set of independent variables are changes from $t-1$ to $t$ of the term yield spread (TERM, the difference between the 10-year interest rate and the 1-month T-Bill rate), the default spread (DEF, the difference between the 30-year treasury yield and the yield on a Baa corporate bond), the aggregate market dividend yield (DY), the credit spread (Credit, the difference between the Baa and the Aaa corporate bond yields), the financial distress index (Distress, a synthetic indicator of financial distress in the U.S.), the aggregate price-earnings ratio (PE), the market uncertainty index (Mkt Unc) from Baker et al. (2014), and the VIX index. Data are from the FredII database of the St Louis Fed and the Chicago Board Options Exchange (CBOE). The sample period is 05/10/1996-10/31/2014, daily. Panel A shows the estimated betas and Panel B the marginal effects. *** means statistical significance at the 1% confidence level, ** significance at the 5% confidence level and * significance at the 10% level.

Panel A: Betas

<table>
<thead>
<tr>
<th></th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
<th>M9</th>
<th>M10</th>
<th>M11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.335***</td>
<td>-0.332***</td>
<td>-0.335***</td>
<td>-0.334***</td>
<td>-0.334***</td>
<td>-0.325***</td>
<td>-0.332***</td>
<td>-0.335***</td>
<td>-0.335***</td>
<td>-0.330***</td>
<td></td>
</tr>
<tr>
<td>Term</td>
<td>0.656***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit</td>
<td></td>
<td>2.321***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Default</td>
<td></td>
<td></td>
<td>1.998***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DY</td>
<td></td>
<td></td>
<td></td>
<td>0.306</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.021</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distress</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.424***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt Unc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
<td></td>
<td></td>
<td>-0.002</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.01</td>
<td>0.03</td>
<td>0.12</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.09</td>
<td>0.01</td>
<td>0.14</td>
<td>0.15</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Panel B: Marginal Effects

<table>
<thead>
<tr>
<th></th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
<th>M9</th>
<th>M10</th>
<th>M11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term</td>
<td>0.248</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit</td>
<td></td>
<td>0.875</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Default</td>
<td></td>
<td></td>
<td>0.798</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DY</td>
<td></td>
<td></td>
<td></td>
<td>0.115</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distress</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.261</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt Unc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
<td></td>
<td>-0.001</td>
</tr>
</tbody>
</table>
Table 6. Systemic Risk and Financial Distress

Systemic risk and financial distress indicators. This table reports the results from a robust regression analysis where the dependent variable is the St. Louis Fed Financial Stress Index (Distress). Panel A shows the results with using as independent variables contemporaneous and lagged values of the model implied systemic risk indicator \( c_t \). Panel B shows the same regressions using current and lagged values of the log of the probability of contagion (LogProb). Data are from the Fred II database of the St Louis Fed. The sample period is 05/10/1996-10/31/2014, daily. *** means statistical significance at the 1% confidence level, ** significance at the 5% confidence level and * significance at the 10% level. Standard errors are corrected for heteroskedasticity and autocorrelation in the residuals (Newey-West HAC)

Panel A: Systemic Risk Indicator (Dep: Distress)

<table>
<thead>
<tr>
<th></th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.501***</td>
<td>-0.512***</td>
<td>-0.522***</td>
<td>-0.001</td>
<td>-0.014</td>
<td>-0.007</td>
<td>-0.012</td>
<td>-0.013</td>
</tr>
<tr>
<td>( c_t )</td>
<td>1.329***</td>
<td></td>
<td></td>
<td>0.033***</td>
<td>0.023***</td>
<td>0.025***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( c_{t-1} )</td>
<td>1.331***</td>
<td></td>
<td></td>
<td></td>
<td>0.017**</td>
<td>0.014*</td>
<td>0.034**</td>
<td></td>
</tr>
<tr>
<td>( c_{t-2} )</td>
<td></td>
<td>1.341***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.028</td>
</tr>
<tr>
<td>Distress (-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.982***</td>
<td>0.981***</td>
<td>0.983***</td>
<td>0.982***</td>
</tr>
<tr>
<td>adj ( R^2 )</td>
<td>0.37</td>
<td>0.35</td>
<td>0.37</td>
<td>0.95</td>
<td>0.92</td>
<td>0.94</td>
<td>0.96</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Panel B: Log of Contagion Probability (Dep: Distress)

<table>
<thead>
<tr>
<th></th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.772***</td>
<td>0.776***</td>
<td>0.778***</td>
<td>-0.001</td>
<td>0.018</td>
<td>0.016</td>
<td>-0.012</td>
<td>0.019</td>
</tr>
<tr>
<td>LogProb</td>
<td>0.208***</td>
<td></td>
<td>0.778***</td>
<td></td>
<td>0.001</td>
<td>0.016</td>
<td>-0.012</td>
<td>0.019</td>
</tr>
<tr>
<td>LogProb(-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.005**</td>
<td>0.006**</td>
<td>0.006***</td>
<td></td>
</tr>
<tr>
<td>LogProb(-2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.201***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distress (-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.982***</td>
<td>0.982***</td>
<td>0.983***</td>
<td>0.982***</td>
</tr>
<tr>
<td>adj ( R^2 )</td>
<td>0.41</td>
<td>0.42</td>
<td>0.43</td>
<td>0.95</td>
<td>0.95</td>
<td>0.94</td>
<td>0.97</td>
<td>0.95</td>
</tr>
</tbody>
</table>
Figure 1. Simulation Results

Simulation results. This figure plots the estimation results on a simulated dataset as explained in Section 2. Panel A compares the estimated adjacency matrix (right) to the true network (left). The length of the time series simulation is $T = 1000$ and the asset span is $p = 20$. We assume the existence of two systemic risk states and a single source of systematic risk which is independent of the rest, $x_t \sim i.i.d. N(0, 1)$. Panel B shows the results of the Stein Loss as computed from (18) with $\hat{\Sigma}$ and $\Sigma$ the estimated and true residuals covariance structure, respectively. We conduct the experiment for different sample sizes, $T = 50, 100, 200$, with $p = 20$ assets and considering a single factor as above. Our model performance is compared with a standard Seemingly Unrelated Markov Switching regression model.
Figure 2. Probability of High Systemic Risk

Systemic Risk Probability. This figure shows the model-implied probability of high systemic risk (i.e. high contagion). The gray area represents the probability of being in a contagion state, while the red line shows the NBER recession indicator for the period following the peak of the recession to through the through. The sample period is 05/10/1996-10/31/2014, daily.

Figure 3. Transition Probabilities of Systemic Risk

This figure plots the transition probabilities of systemic risk. The sample period is 05/10/1996-10/31/2014, daily. The first three columns represent the probability of staying in a state of low systemic risk computed from the three-factor Fama-French model, the CAPM and the I-CAPM, respectively. The last three columns represent the probability of staying in a state of high systemic risk computed from the three-factor Fama-French model, the CAPM and the I-CAPM, respectively.
Figure 4. Changes in Exposures to Systematic Risks - Low vs High Systemic Risk, Three-Factor Model

Conditional alphas and betas. This figure reports changes in the conditional intercepts and exposures to sources of systematic risks for each of the stock in the sample. Top left panel shows the so-called Jensen’s alpha. Top right panel reports the exposure to market risk (excess return on aggregate wealth). Bottom left and right panel report the firms exposures on the size and value effects as originally proposed in Fama and French (1993). The sample period is 05/10/1996-10/31/2014, daily.
Figure 5. Changes in Exposures to Systematic Risks - Low vs High Systemic Risk, I-CAPM

Conditional alphas and betas. This figure reports the changes to conditional intercepts and exposures to sources of systematic risks for each of the stock in the sample. Top left panel shows the so-called Jensen’s alpha. Top right panel reports the exposure to market risk (excess return on aggregate wealth). Bottom left and right panel report the firms exposures on the default and aggregate dividend yield. The sample period is 05/10/1996-10/31/2014, daily.
Figure 6. Network Connectedness: CAPM

Network connectivity conditioning for market risk. This figure reports the network structure computed conditioning for market risk. Top panel shows the network connectedness when systemic risk, or contagion, is low. Bottom panel shows the structure of the network when systemic risk increases.
Figure 7. Network Connectedness: Three-Factor Model

Network connectivity conditioning for market risk, size and value. This figure reports the network structure computed conditioning for additional sources of systematic risk such as size and value. Top panel shows the network connectedness when systemic risk, or contagion, is low. Bottom panel shows the structure of the network when systemic risk increases.

(a) Panel A: Low Systemic Risk

(b) Panel B: High Systemic Risk
Figure 8. Network Connectedness: I-CAPM

Network connectivity from an I-CAPM implementation. This figure reports the network structure computed conditioning for additional sources of systematic risk such as default and term spread, and aggregate dividend yield. Top panel shows the network connectedness when systemic risk, or contagion, is low. Bottom panel shows the structure of the network when systemic risk increases.
Figure 9. Eigenvector Centrality Across Companies

Eigenvector centrality. This figure plots the median eigenvector centrality sorted for the top 20 companies for both low and high systemic risk. Top panel report the results obtained conditioning for aggregate market risk only. Mid panel shows the results obtained considering in addition size and value systematic risks. Bottom panel shows the results computed from an implementation of an I-CAPM model.

(a) Panel A: CAPM with Low and High Systemic Risk

(b) Panel B: Three-factor Model with Low and High Systemic Risk

(c) Panel C: I-CAPM with Low and High Systemic Risk
Figure 10. Relative Market Values of the Industries

Relative market values. This figure reports the market value of each industry relative to the rest of the economy. Industry classification is based on the Global Industry Classification Standard (GICS) developed by MSCI. The sample period is 05/10/1996-10/31/2014, daily.
Figure 11. Systemic Risk, Financial Distress and Stock Predictors

Systemic risk and financial variables. This figure reports the time series of the model-implied probability of high systemic risk (top left panel), together with a set of financial predictors. The set of variables considered are: the St. Louis Fed Financial Stress Index (top middle panel), the VIX index (top right panel), the default spread (DEF, bottom left panel, measured as the difference between the 30-year treasury yield and yield on a Baa corporate bond), the term yield spread (TERM, bottom middle panel, measured as the difference between the 10-year interest rate and the 1-month T-Bill rate), and the aggregate dividend yield (DY, bottom right panel). Data are from FredII database of the St. Louis Fed and the Chicago Board Options Exchange (CBOE). The sample period is 05/10/1996-10/31/2014, daily.