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Early warnings of systemic risk using one-minute high-frequency data

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ABSTRACT

This study uses high-frequency principal component analysis (HF PCA) to extract information from stock prices to monitor and measure systemic risk in the financial system. The empirical analysis carried out in this study using one-minute returns of stocks included in the Russel 3000 index from 2003 to 2021 shows a clear relationship between the size of the realized eigenvalues and systemic increases in financial stress. We also found that realized eigenvectors can trace the role of firms/sectors as potential sources of financial stress in different periods. We measured the transmission of shocks from (to) the financial sector to (from) other sectors and the real economy. This provides a tool for analyzing the spread of this financial instability that could affect the functioning of the financial system to the extent that the real economy is seriously damaged. HF PCA is a risk identification framework that allows policymakers and central banks to detect risks in real-time and address potential threats to financial stability with the most appropriate policy tools.

1. Introduction

Systemic risk arises when widespread financial instability materializes. This instability is characterized by a fragile financial system[1] incapable of efficiently channeling savings to investments (financial intermediation). When this fragility becomes systemic, economic growth and overall well-being suffer substantially (De Bandt and Hartmann, 2000; De Bandt, Hartmann, and Peydró, 2012; ECB, 2009). Systemic crises often erupt from initial adverse shocks that propagate and amplify throughout the financial system. A prime example is the August 2007 event where BNP Paribas halted redemptions on funds heavily exposed to illiquid subprime mortgage-backed securities. This localized issue in a single asset class triggered a true "systemic event" across the global financial system. The severity of such crises hinges on the interconnectedness of financial institutions and markets. Stronger links can amplify shocks and their spillovers throughout the system, as witnessed during the Great Financial Crisis. The complex interplay of large shocks, their propagation, feedback loops, and amplification makes financial crisis modeling and risk forecasting a significant challenge.

In this paper, we use one-minute market prices to identify systemic risks stemming from the codependent behaviors and chain reactions of financial institutions. Our view is grounded in the widespread perception that market prices embed all publicly available information about financial institutions' assets and liabilities and their risks, as well as the implications deriving from institutions' interconnections (leading to common exposures to extreme stress events). When analyzing the level of stress in the financial system it would be challenging to deal with the whole system, which in the real world is a very complex and complicated network of financial markets, financial intermediaries, and financial infrastructures with all playing a crucial role for the stability properties of the system. Our dataset focuses on U.S. financial institutions by comprising stocks from the Russell 3000 index across three key industry groups: banks, financial services, and insurance. These groups, categorized within the Russell 3000's Monetary Financial Institutions, Other Financial Institutions, and Insurance Corporations and Pension Funds sectors, represent a critical segment of the financial system, historically playing a central role during events like the Great Recession.

The recent financial crisis has fueled the literature on systemic risk, which, according to Cerutti, Claessens, and McGuire (2012), is often divided into three broad categories. The first strand of research

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[1] According to the ESA 2010, European system of accounts, (Eurostat, 2013), the financial system comprises monetary financial institutions (central banks, commercial banks, savings banks, and credit unions), non-money market investment funds (investment pools of assets like stocks, bonds, and real estate), insurance corporations and pension funds and other financial institutions (financial leasing companies, venture capital firms, financial brokers, and captive financial institutions) [(Eurostat, 2013), European system of accounts 2010, Luxembourg].

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focuses on how balance sheet linkages amplify shocks (De Haas and Van Horen, 2011). A second part of the literature has traditionally focused on taking advantage of market prices (see two recent surveys by Benoit, Colliard, Hurlin, & Pérignon, 2017; Silva, Kimura, & Sobreiro, 2017) for systemic risk measurement. Finally, a third group of research takes a forward-looking perspective that relies on simulations (e.g., Espinosa-Vega and Solé, 2011). Our article is more closely related to the empirical literature that uses information on market prices to measure systemic risk, such as Acharya, Pedersen, Philippon, and Richardson (2017), Adrian and Brunnermeier (2016), Bisias, Flood, Lo, and Valavanis (2012), Brownlees and Engle (2017), Caporin, Garcia-Jorcano, and Jimenez-Martin (2021), Cerchiello and Giudici (2016), and Dabrowski, Beyers, and de Villiers (2016). We complement this literature, which relies mainly on daily or lower frequency returns, using high-frequency (HF) prices of stocks. Our generalization leads to more accurately capturing the multiple dimensions of systemic risk.

The systemic risk has multiple dimensions. It shows a time-varying pattern, which follows the build-up of financial imbalances over time, and a cross-sectional structure, which determines the degree of fragility of the system and governs its resilience to shocks. Financial shocks are endogenously driven, as they are derived from the codependent behaviors and chain reactions of the financial institutions themselves. The time-varying and cross-sectional dimensions of risk are compounded during the run-up to a crisis. On the one hand, systemic risk is correlated with the procyclicality of the agent's behavior; it is dynamic in nature, and it can be detected only through observation over long time spans. This is the time-varying dimension of systemic risk (Borio, 2013; Borio and Lowe, 2002a, 2002b; Borio and Drehmann, 2009; Brunnermeier, 2001; Kiyotaki and Moore, 1997). On the other hand, systemic risk is also correlated with the structure of interlinkages within the system. In this sense, an accurate assessment of systemic risk requires not only adequately capturing the time-varying dimension of financial aggregates, but also a description of the specific structure of the banking/financial interconnection at each point in time, which is the cross-sectional dimension of systemic risk.

The availability of HF data provides the opportunity to analyze short periods independently and identify the time-varying nature and strength (vulnerability) of direct and indirect links within a financial network with much less statistical uncertainty. Our study contributes to the literature that uses new econometric techniques to predict systemic risk using HF data. Interest in HF observations emerged largely from Andersen and Bollerslev (1998)'s study, which showed that asset price can be assumed to follow a continuous-time diffusion process and that it is common to use HF data to accurately forecast asset price volatility (see, for example, Degiannakis and Floros, 2016; Caporin and Velo, 2015; Liu, Patton, and Sheppard, 2015; Kotkatvuori-Örnberg, 2016). However, there are not many studies that analyze systemic risk using HF data. Jain, Jain, and McInish (2016) focused on how HF quoting (HFQ) affects systemic risk. Although HFQ can increase volatility, it is not clear if it affects the severity of losses from episodic illiquidity, and in a cascade setting, it leads to an increase in systemic risk. A relevant event analyzed in multiple studies is the Flash Crash of May 2010 in the United States (Cartea and Penalva, 2012; Easley, De Prado, and O'Hara, 2011; Jarrow and Protter, 2011). Sánchez Serrano (2021) indicated that the increased use of technology has contributed to the rapid growth of trading in stock markets in recent decades, increasing the number of participants and a sharp decline in the price of information. HF trading (HFT) can be seen as a manifestation of this development. The article highlights that systemic vulnerabilities related to HFT, such as adverse selection in orders that can potentially crowd out non-HFT market makers in times of stress, could create systemic risk, and several scholars have discussed the introduction of a limit in the speed of trading to address this phenomenon.

By analyzing both dimensions, this study contributes to the identification of systemic stress and the channels through which it spreads in its early stages to facilitate the avoidance of the adverse consequences of internal shocks that are magnified within the network. Here, the measurement challenge is to identify when a financial network is potentially vulnerable and the nature of disruptions that can trigger a problem. To do so, this study considered two key elements simultaneously combining the two fields of high-frequency (HF) econometrics and large-dimensional factor analysis. These tools allow for time variation in the factor structure that explains the internal interconnection of a large-dimensional panel dataset.

We worked directly on a large cross-section of individual stocks, and principal component analysis (PCA) turned out to be one of the most popular techniques when analyzing large datasets. Fundamentally, this approach aims to compress as much data content as possible into a small number of principal components (PCs) that summarize a large part of the variation of the data. Bai (2003) developed an inferential theory for factor models for a large cross-section and a long horizon based on PCA. It is also widely accepted in the financial literature that financial markets can be described by a small number of factors derived from PCA. For example, Litterman and Scheinkman (1991) used PCA to identify a three-factor structure in the term structure of bond yields, labeled as the level, slope, and curvature factors. Egloff, Leippold, and Wu (2010) identified two volatility factors on the PCA of variance swaps. Several authors have also introduced PCA to summarize the informative content of different systemic risk measures (see Caporin, Costola, Garibal, and Maillet, 2022; Fang, Xiao, Yu, and You, 2018; Giglio, Kelly, and Pruitt, 2016; Nucera, Schwaab, Koopman, and Lucas, 2016). Rodríguez-Moreno and Peña (2013) also used classical PCA to compare monthly macro- and micro-market-based systemic risk measures, highlighting that measures based on credit default swaps outperform others based on interbank rates of stock prices. Although we shall not build on these directly, other important papers on PCA and systemic risk, including Billio, Getmansky, Lo, and Pelizzon (2012) and Carlson, Lewis, and Nelson (2014), employ correlation-based PCA to construct some measures of financial connectedness and stress, respectively. Other studies (Hakkio & Keeton, 2009; Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010; Hollo, Kremer, & Lo Duca, 2012; Illing & Liu, 2006; Louzis & Vouldis, 2012; Morales & Estrada, 2010) proposed factor analysis using PCA to emphasize the selection of variables in the development of systemic stress indicators, which is driven primarily by the need to reflect stress conditions in all dimensions related to the functioning of the financial system.

The classic PCA approach to the statistical inference of eigenvalues suffers from the curse of dimensionality. The number of parameters increases much faster than the cross-sectional size, requiring years of time-series data for estimation, raising issues of survivorship bias, potential non-stationarity, and parameter constancy. HF PCA is expected to improve the classic approach in several dimensions. In fact, HF PCA is capable of (1) dealing with the growing number of parameters when the cross-sectional dimension increases, (2) eliminating stationary conditions, allowing both time-varying volatility (Ait-Sahalia and Xiu, 2017) and jumps in the log-price processes (Pelger, 2019, 2020), and (3) capturing potentially nonlinear relationships thanks to the local estimation of the PC.

This article faces issues that are similar to other papers using HF data, which have unique characteristics that are absent in the data measured at lower frequencies. Analysis of these data poses interesting and unique challenges to econometric modeling and statistical analysis. Specifically, several authors (Ponta, Trinh, Raberto, Scalas, and Cincotti, 2019, Zhang, 2016, among others) identify the difficulties in modeling high-frequency data from a statistical perspective. In this sense, in this paper, we do not adhere to strong parametric assumptions that are required in a low-frequency setting. The high-frequency asymptotic framework allows for a nonparametric analysis of general stochastic processes. Our research is based on Aït-Sahalia and Xiu (2017, 2019) that, extending the PCA to the high-frequency continuous-time framework, provides asymptotic properties for the realized eigenvalues and eigenvectors assuming a general Ito semimartingale for modeling the stock returns.

Therefore, we combined HF econometrics and large-dimensional factor analysis using PCA to approximate the informative content of an HF dataset. We first track and measure systemic stress by estimating and analyzing the dynamic behavior of realized eigenvalues and eigenvectors using (Ait-Sahalia & Xiu, 2017) large-dimensional HF factor model. We also want to trace how the rich set of information that stock prices contain propagates other markets and to understand whether the information embedded in the comovement among stock prices could help predict future financial instability and crises. Therefore, an additional challenge is to measure the transmission of shocks from (to) the financial sector to (from) other sectors and the real economy through a selection of systemic risk indicators using the Diebold–Yilmaz methodology. Diebold and Yılmaz (2009, 2012, 2014) evaluated the volatility spillover within the financial market by focusing on the realized volatility sequences. Their proposal is now among the most studied tools for the analysis of systemic risk and risk spillover among assets or, in general, financial markets and instruments. Their contribution provides us with a methodology to analyze the spread of financial instability that could affect the functioning of the financial system. In turn, this instability could reach the point where the real economy is seriously impacted, which is notably one of the definitions of systemic risk (ECB, 2010; De Bandt and Hartmann, 2000; De Bandt et al., 2012). In the first step, we pointed to understanding the informative content of the realized quantities, while in the second step, we determined the relationship between these quantities and systemic risk.

The analyses we developed contribute to the scarce literature that focuses on the use of HF factors to capture systemic stress in the financial market. Although this framework has been widely used to estimate and interpret the factor structure of stock prices, this work is pioneering in using one-minute data to analyze systemic risk. For example, Alexeev, Dungey, and Yao (2017), and Bollerslev, Li, and Todorov (2016) estimated the betas of a continuous and jump market factor, while Pelger (2019) identified an unknown factor structure for the S&P 500 firms. This study went further and used an HF PCA approach to continuously capture the time-varying relationship that might exist in the financial system. In turn, this allowed for a precise estimate of the financial distress of the system and its transmission to other markets. HF information extracted from available data would allow regulators and policy authorities to act in time and monitor the effectiveness of implemented policies and reactions, taking advantage of diagnostic tools that, in addition to being reliable, must be available within a useful time span.

The empirical analysis makes use of one-minute returns for the financial stocks included in the Russel 3000 index and available from January 2003 to February 2021. Due to the delisting of a few companies after the Lehman default, we separately analyzed two subsamples, setting the split at September 16, 2008. We evaluated the realized eigenvalues and eigenvectors on a weekly basis, following Ait-Sahalia and Xiu (2017). We found evidence supporting the relevance of the first three PCs, whose patterns can be related to known events: the Lehman collapse, the Brexit referendum, US and EU monetary policy announcements, and the surge of the COVID-19 pandemic. Increased relevance of dominant PCs indicates a higher level of comovement among stocks and an increase in the degree of fragility of the system. Therefore, there is a clear relationship between eigenvalues and systemic increases in financial stress. We also found that realized eigenvectors can trace the role of firms/sectors as potential sources of financial stress in different periods of time. This occurs when the composition of the eigenvectors is considered and attributed, for instance, to economic sectors or to single companies. The loading biplots show the leading performance of AIG (American Insurance Group), FRE (Freddie Mac), FNM (Fannie Mae), and LEH (Lehman Brothers) during the 2008 financial crisis and provide further insight into the informative content of realized PCA. Finally, when moving to the evaluation of the spillover, our analyses show that severe financial crises are preceded by high volatility levels – that is, higher financial stress – suggesting the potential role of HF PCA for the construction of early warning indicators of systemic risk.

The remainder of the paper is organized as follows. Section 2 briefly summarizes the methodology. Section 3 describes the data, reviews the estimation of realized eigenvalues and eigenvectors, and shows the empirical eigenvalues and eigenvectors. Section 4 focuses on loading plots and their interpretation. Section 5 moves to the evaluation of the spillover effect between realized PCs, and Section 6 concludes the paper.

2. Methodology

In Section 2.1, we describe briefly the methodology proposed by Aït-Sahalia and Xiu (2017, 2019) on PCA for continuous-time stochastic processes using one-minute data that we used to combine high-frequency analysis and systemic risk, and in Section 2.2, we summarize the well-known methodology introduced by Diebold and Yılmaz (2009, 2012, 2014) that we employed to track spillovers to other sectors and the real economy through information extracted from financial markets by adopting PCA on high-frequency data.

2.1. Principal components with high-frequency data

HF data allow for the precise construction of time-varying eigenvalues, eigenvectors, and PCs. HF PCA using spectral functions is well documented by Aït-Sahalia and Xiu (2017, 2019), to whom we refer for a detailed description of the complete methodology. Although this research is based solely on Aït-Sahalia and Xiu (2017, 2019), other important papers on HF PCA and factor analysis are (Kong, 2017) and Pelger (2019, 2020). In this section, we briefly review Aït-Sahalia and Xiu's methodology — which is the pillar upon which we build the empirical analysis carried out in the remainder of this paper.

2.1.1. Realized principal components

We assume that the vector X_j includes the logarithmic prices at time j of d quoted companies; time is measured within the interval $[0, t]$, and equidistant observations (over time) are separated by a time interval Δ_n. Returns are calculated as $\Delta_l^n X = X_{l\Delta n} - X_{(l-1)\Delta n}$ samples each minute on a one-week horizon. Note that $[0, t]$ is the time interval considered in our sample, with $t = 1950/(390 \cdot 252) = 0.0198$ years in a week, where 1950 are the minutes in a week, 390 are the minutes in a day, and 252 are days in a year. Furthermore, Δ_n is the time interval in years in which the data are separated into $[0, t]$, in our case $\Delta_n = 1/(390 \cdot 252) = 0.000010175$ years in 1 min. To avoid the adverse effects of microstructure noise (bid–ask bounces, discreteness of prices, information asymmetries or transaction costs) and asynchronicity we follow (Aït-Sahalia & Xiu, 2019) and use a one-minute sampling frequency (relatively sparse), instead of tick-by-tick ultrahigh frequency data. (The market microstructure noise of one-minute data is not a serious problem for liquid stocks, which typically trade on the infra-second time scale). Aït-Sahalia and Xiu (2019) show both in simulation and empirically that HF PCA works relatively well using one-minute returns. In addition, given the returns observed within a week, we form non-overlapping blocks of length $k_n\Delta_n$, each containing $k_n = 325$ observations to mitigate the possible effect of microstructure.[2] We obtained a suitable block length considering the trade-off between mitigating microstructure noise and reducing dimensionality (ratio of the cross-sectional dimension against the number of observations). To conclude, we also note that the use of companies with large market value, which are highly traded, reduces the impact of asynchronicity

[2] Following Aït-Sahalia and Xiu (2017, 2019), we fixed k_n to be closest divisors of $[t/\Delta_n]$ to $\theta\Delta_n^{-1/2}\sqrt{log(d)}$, with $\theta = 0.5$ and d is the dimension of X, which is the number of quoted companies.

and, at the same time, further mitigates the impact of microstructure noise.[3] At each $ik_n\Delta_n$, for $i = 1, \dots, m$, with m being the number of blocks in a week, following (Aït-Sahalia & Xiu, 2019), we estimate the realized covariance $c_{ik_n\Delta_n}$ by

$$\hat{c}_{ik_n\Delta_n} = \frac{1}{k_n\Delta_n}\sum_{j=1}^{k_n}(\Delta^n_{ik_n+j}X)(\Delta^n_{ik_n+j}X)^T. \tag{1}$$

where the *hat* identifies an estimated quantity.

From the block-specific spot realized covariance, $c_i \equiv c_{ik_n\Delta_n}$ in Eq. (1), with $i = 1, \dots, m$, we estimated the eigenvalues $\lambda_{g,i}$ and the eigenvectors, $\gamma_{g,i}$, which allowed us to construct the corresponding PCs. If $\gamma_{g,i}$ is the eigenvector that corresponds to the eigenvalue of $\lambda_{g,i}$, the gth PC for a given week is equal to

$$\sum_{i=1}^{[t/(k_n\Delta_n)]-1}\gamma^T_{g,(i-1)k_n\Delta_n}(X_{(i+1)k_n\Delta_n} - X_{ik_n\Delta_n}) \tag{2}$$

where $t/(k_n\Delta_n) = m$ is the number of blocks in a week (time interval considered), in our case 6 blocks. We stress that the last equation is based on the log-price and not on the log-return.

2.1.2. Realized eigenvalues

We estimated the eigenvalues of $\hat{c}_{ik_n\Delta_n}$ by solving for the roots of $|\hat{c}_{ik_n\Delta_n} - \lambda\mathbb{I}| = 0$. We have $\lambda(\hat{c}_{ik_n\Delta_n}) = \hat{\lambda}_{ik_n\Delta_n}$. The eigenvalues stacked in $\hat{\lambda}_{ik_n\Delta_n}$ are almost surely distinct, so we have $\lambda_{1,ik_n\Delta_n} > \lambda_{2,ik_n\Delta_n} > \dots > \lambda_{d,ik_n\Delta_n}$. The estimator of the integrated eigenvalues vector is given by

$$V(\Delta_n, X, \lambda) = k_n\Delta_n\sum_{i=0}^{[t/k_n\Delta_n]}\lambda(\hat{c}_{ik_n\Delta_n}) \tag{3}$$

which is consistent.[4]

Since there is a second-order asymptotic bias associated with the estimator shown in Eq. (3), obtaining a central limit theorem for that is more involved. From the characterization of the bias, Aït-Sahalia and Xiu (2019) suggested a bias-corrected estimator as follows[5]

$$\tilde{V}(\Delta_n, X; F^\lambda_p) = \frac{k_n\Delta_n}{g_p - g_{p-1}} \times \sum_{i=0}^{t/(k_n\Delta_n)}\sum_{h=g_{p-1}+1}^{g_p}\left\{\hat{\lambda}_{h,ik_n\Delta_n} - \frac{1}{k_n}Tr\left((\hat{\lambda}_{h,ik_n\Delta_n}\mathbb{I} - \hat{c}_{ik_n\Delta_n})^+\hat{c}_{ik_n\Delta_n}\right)\hat{\lambda}_{h,ik_n\Delta_n}\right\} \tag{4}$$

where $F^\lambda_p(A)$ denotes the pth entry of the corresponding spectral function F^λ for any matrix $A \in \mathcal{M}^+_g$ defined by $(f \circ \lambda) = \frac{1}{g_l - g_{l-1}}\sum_{j=g_{l-1}+1}^{g_l}\lambda_j(A)$ for $1 \le g_{l-1} < g_l \le d$, and $Tr(A) = (f_1 \circ \lambda)(A)$ is the trace for any matrix $A \in \mathcal{M}^+_g$, where $f_1(x) = \sum_{j=1}^d x_j$ is its associated symmetric function for any $x \in \mathbb{R}^+_d$. The superscript + denotes the Moore–Penrose inverse of a real matrix.

2.1.3. Realized eigenvectors

As Aït-Sahalia and Xiu (2019) noted, when eigenvalues are simple, the corresponding eigenvectors are uniquely determined. Once we constructed the PC and estimated the realized eigenvalues, we proceeded with the evaluation of the loadings of each entry of X on each PC. We determined the sign and, hence, identified the eigenvector by requiring, a priori, a certain entry of the eigenvector to be positive, for example, the first nonzero entry.

Notice that $\gamma_{g,s}$ is a vector-valued function that corresponds to the eigenvector of c_s with respect to a simple root $\lambda_{g,s}$, for each $s \in [0, t]$, and using the results in Aït-Sahalia and Xiu (2019), it follows that the bias-corrected eigenvector estimator corresponds to

$$k_n\Delta_n\sum_{i=0}^{[t/(k_n\Delta_n)]}\left(\hat{\gamma}_{g,ik_n\Delta_n} + \frac{1}{2k_n}\sum_{p\neq g}\frac{\hat{\lambda}_{g,ik_n\Delta_n}\hat{\lambda}_{p,ik_n\Delta_n}}{(\hat{\lambda}_{g,ik_n\Delta_n} - \hat{\lambda}_{p,ik_n\Delta_n})^2}\hat{\gamma}_{g,ik_n\Delta_n}\right) \tag{5}$$

2.2. Financial stress spillovers

Following the methodology introduced by Diebold and Yilmaz (2012), we studied the transmission of shocks from (to) stocks of the financial sector to (from) other nonfinancial sectors and the real economy. In what follows, we describe the empirical framework we followed to identify spillover effects between volatility in the stock prices of the US financial sector and the commonly used macrofinance uncertainty indicators.

We used a vector autoregressive framework in which the forecast error variance decomposition is invariant to the variable ordering (Koop, Pesaran, and Potter, 1996; Pesaran and Shin, 1998), and we explicitly included directional volatility spillovers between the realized eigenvalues and the previously described stress and risk indicators, using the methodology proposed by Diebold and Yilmaz (2012).

Consider a covariance stationary N-variable VAR(p), with an associated infinite moving average representation, $x_t = \Theta(L)\varepsilon_t$, with $\Theta(L) = I + \sum_{j=1}^\infty \Theta_j L^j$, and $E(\varepsilon_t\varepsilon'_t) = \Sigma$. The forecast error variance decomposition allowed us to decompose the forecast error variances of each variable as follows:

$$\delta_{ij} = \frac{\sigma^{-1}_{jj}\sum_{h=0}^{H-1}\left(e'_i\Theta_h\Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e'_i\Theta_h\Sigma\Theta'_h e_i\right)}$$

where $\sigma_j j$ is the j−th element of the diagonal of the Σ matrix and e_j is a selection vector, with one in the jth position and zeros otherwise. Because shocks in the variance decomposition framework are not orthogonal, the sum of variance contributions of the forecast error is not necessarily equal to one, that is, $\sum_{j=1}^N \delta_{ij} \neq 1$. Therefore, in the calculation of the spillover index, we normalized the variance decomposition matrix on a row basis by setting

$$\tilde{\delta}_{ij} = \frac{\delta_{ij}}{\sum_{j=1}^N \delta_{ij}}.$$

By construction, $\sum_{j=1}^N \tilde{\delta}_{ij} = 1$, and $\sum_{i,j=1}^N \tilde{\delta}_{ij} = N$.

The variance decomposition allowed us to assess the fraction of the H-step-ahead error variance that is due to shocks to the other variables included in the system. As Diebold and Yilmaz (2012), we fixed a priori the order of the VAR model and chose $p = 4$; this leads to a lag structure that lasts about a month. Moreover, we focus on predictions for up to two weeks and thus set $H = 2$.[6]

We define $S_{i\leftarrow j} = \tilde{\delta}_{ij}$ as the cross-variance shares of spillovers, that is, the fraction of the error variance of the H step ahead in the forecast x_i that is due to shocks to x_j, for $i, j = 1, 2, \dots, N$, such that $i \neq j$. Note

[3] Another procedure for noise-robust estimates of the instantaneous eigenvalues and eigenvectors is based on the instantaneous version of the smoothed two-scales realized volatility (S-TSRV) developed by Mykland, Zhang, and Chen (2019). S-TSRV combines the Two Scales Realized Volatility (TSRV) by Zhang, Mykland, and Aït-Sahalia (2005) and pre-averaging constructions (take weighted local averages of the data (log prices) before taking squares developed by Jacod, Li, Mykland, Podolskij, and Vetter, 2009, to derive a solution to controlling edge effects for handling asynchronously observed multivariate data.) to derive a solution to controlling edge effects for handling asynchronously observed multivariate data.

[4] See Aït-Sahalia and Xiu (2019) for more details, especially about asymptotic theory.

[5] Aït-Sahalia and Xiu (2019) proposed another version of the bias-corrected estimator in the event that we are only interested in the spectral function that depends on one simple eigenvalue. They introduced an additional assumption for this scenario, which is weaker than the scenario described in this paper, perhaps the most relevant scenario in practice, which is for spectral functions that depend on all eigenvalues. For more details, see Aït-Sahalia and Xiu (2019).

[6] We perform a robustness check for the sensitivity of the results to the choice of the order of the VAR or of the forecast horizon. We calculate the spillovers for orders from 2 to 7 and for forecast horizons varying from 1 to 4 weeks. We find that spillovers are not sensitive to the choice of the order of the VAR or to the choice of the forecast horizon.

Table 1
Summary statistics for 1-min returns on 5 trading-day blocks of the different industry groups – banks, financial services, and insurance firms – all of the financial institutions for the period before LEH bankruptcy: January 10, 2003–September 16, 2008, and after the LEH bankruptcy: September 23, 2008–February 23, 2021. Each statistic is calculated as the average of the statistics obtained for each stock's market returns using returns sampled every $\Delta_n = 1$ min over a 5 consecutive trading days horizon. In parentheses, in bold, is the number of companies in each period and each sector.

	1-min returns on 5-trading day blocks						
	Mean	Median	St. Deviation	Skewness	Kurtosis	Max	Min
	BANKS						
Before (47)	0.0210	0.0451	3.9322	0.5833	10.3177	21.3012	−16.4071
After (45)	−0.1567	0.0070	4.7791	−0.6776	14.4749	26.4818	−32.5370
	FINANCIAL SERVICES						
Before (26)	0.0739	0.2158	4.5204	−0.6583	10.0025	16.6038	−22.7001
After (22)	0.0813	0.2096	4.6101	−0.5938	12.8714	24.1082	−31.7237
	INSURANCE						
Before (28)	−0.0999	−0.0295	3.5371	−0.2993	9.8814	14.6609	−17.3181
After (26)	−0.0257	0.1375	4.5592	−0.7814	17.1419	26.6179	−33.8664
	ALL						
Before (101)	0.0011	0.0684	3.9741	0.0190	10.1156	18.2511	−18.2796
After (93)	−0.0638	0.0914	4.6776	−0.6868	14.8412	25.9584	−32.7163

that, in general, $S_{i\leftarrow j} \neq S_{j\leftarrow i}$. Therefore, there are $N^2 - N$ spillovers (in our case, 20).

We defined the gross directional volatility spillover received by x_i *from* all other x_j for $i \neq j$, $j = 1, 2, \ldots, N$, as

$$S_{i\leftarrow \cdot} = \sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\delta}_{ij},$$

and the gross directional volatility spillovers transmitted by x_i *to* all other x_j for $i \neq j$, $j = 1, 2, \ldots, N$, as

$$S_{\cdot\leftarrow j} = \sum_{\substack{i=1 \\ i\neq j}}^{N} \tilde{\delta}_{ij}.$$

Hence, there are $2N$ directional volatility spillovers, N 'From Others' and N 'To Others'.

We obtained the net volatility spillover from x_i to all other x_j for $i \neq j$, $j = 1, 2, \ldots, N$ as the difference between the gross volatility shocks transmitted to and those received from all other variables,

$$S_i = S_{\cdot\leftarrow i} - S_{i\leftarrow \cdot}.$$

There are N net volatility spillovers (in our case, 5).

Finally, we calculated the total volatility spillover index which measures the average contribution of volatility shock spillovers across the N variables to the total forecast error variance,

$$S = \frac{1}{N} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\delta}_{ij}.$$

We refer the reader to Diebold and Yilmaz (2012) for additional details on the spillover index construction.

3. High-frequency principal components in the finance sector

3.1. Data description

For the empirical analysis, we worked with intraday returns from 01/10/2003 to 02/23/2021, for a total of 4565 days. Returns are computed as $\Delta_l^n X = X_{l\Delta n} - X_{(l-1)\Delta n}$, and we recall that X is the price log, sampled every minute. Our dataset is made up of the financial institutions' stocks included in the Russell 3000 index, a broad-market index tracking the US exchanges. The stocks we selected belong to three industry groups: banks, financial services, and insurance firms. Furthermore, for our empirical analysis, we divided our dataset into two periods, before and after the LEH bankruptcy. The dataset is made up of intraday returns at one-minute frequency ($\Delta_n = 1$ min), with 390 observations per day and with an horizon T covering 5 trading days. Only 93 of 101 financial institutions originally included in the dataset remained available for the full sample, as eight financial institutions were delisted after September 16, 2008 (LEH bankruptcy). This left us with 101 financial institutions until September 16, 2008 (287 5-day blocks). Of these institutions, 47 are banks, 26 are financial services and 28 are insurance firms. After the LEH bankruptcy, we remain with 93 financial institutions, available for 913 trading blocks of five days (i.e., for the full sample); this restricted dataset includes 45 banks, 22 financial services, and 26 insurance firms. We recovered all data, company prices, and index levels from Kibot.com.[7] Tables A.1–A.2 list the names of the financial institutions in our sample, together with their sector, the latter according to the Thomson Reuters Datastream classification.

Table 1 reports the average of descriptive statistics (mean, median, standard deviation, skewness, kurtosis, max, min) for one-minute returns in the 5-day trading blocks (in %) of the three industries for the period before LEH bankruptcy: January 10, 2003–September 16, 2008, and after LEH bankruptcy: September 23, 2008–February 23, 2021. In general, the returns exhibit stylized characteristics of the daily data: mean and median close to zero, excess kurtosis, and a mild degree of skewness. The three industries and the overall sector showed higher volatility in the second part of the sample and high kurtosis, which is much higher after the LEH bankruptcy. The range max–min is also larger during the second part of the sample; banks (insurance firms) show the largest range before (after) the LEH bankruptcy. Skewness and kurtosis reported in Table 1 would imply distributions with thicker tails than in the Gaussian case.

In rapidly evolving uncertain times (Global Financial Crisis, COVID-19, Silicon Valley Bank collapse), the use of higher frequency data allows rapid estimates and updates of financial stress and, consequently, of systemic risk, mainly under unstable conditions. For example, Chen, Mykland, and Zhang (2020) speculate that building portfolios with an intraday weight update may be an advantage during crisis periods. Many of the established well-known daily or lower frequency indicators used to gauge systemic risk (Acharya et al., 2017; Adrian & Brunnermeier, 2016; Bisias et al., 2012; Brownlees & Engle, 2017) or financial instability cannot keep up with financial conditions that seem to change

[7] Despite being less commonly used than TAQ, the HF data available from Kibot.com have a quality comparable to that of TAQ. A comparison between the data recovered from Kibot and TAQ is available on request.

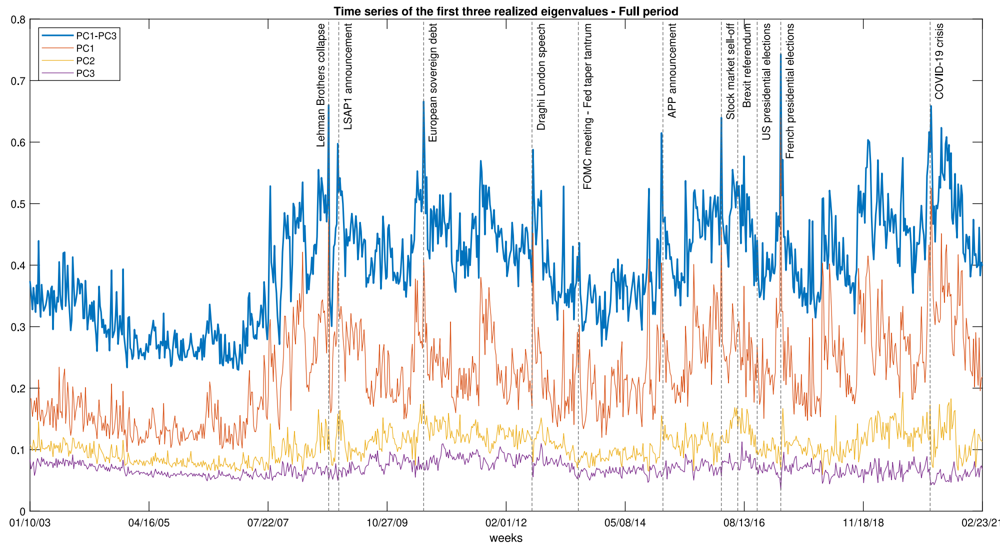

Fig. 1. First three realized eigenvalues. See footnote 8 for the list of events.

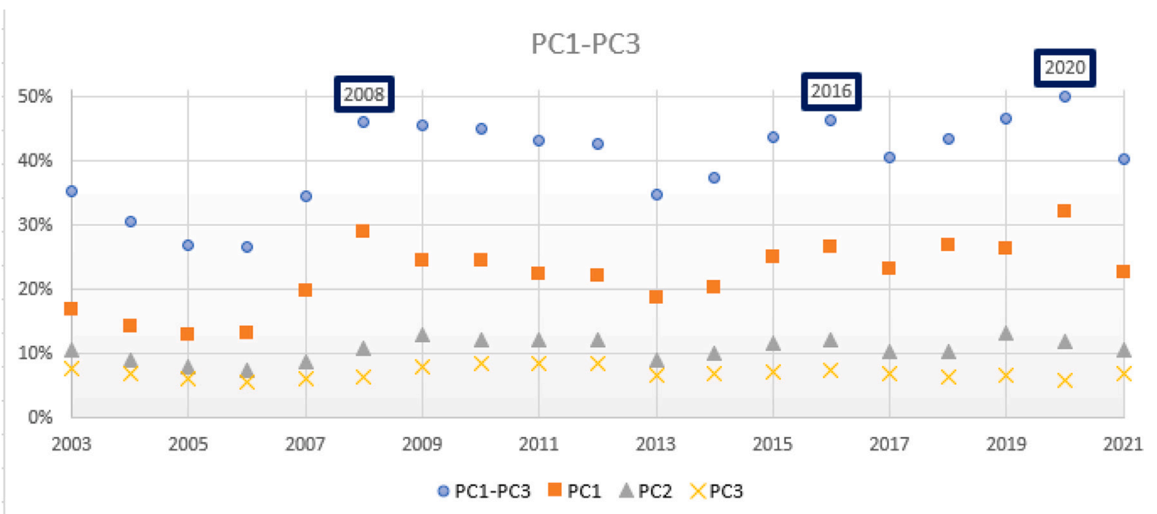

Fig. 2. First three realized eigenvalues. Annual average.

overnight. These indicators usually lag one or more periods behind real-time. HF PCA allows us to quickly identify interconnectedness within a large system to control systemic risk and see how it changes over short-term horizons. We can also analyze how continuous risk factors, which capture the variation during "normal" times, differ from periods of uncertainty.

Therefore, HF PCs provided a useful tool for data analysis that allowed for the identification, in a short period of time, of the cross-sectional interdependence of large multivariate databases. When the evolution of HF PCs over time is analyzed, additional insights might emerge. We started by focusing on the 913 weekly eigenvalues and eigenvectors computed using the methodology described in Sections 2.1.2 and 2.1.3. Traditionally, a higher percentage of the variation explained by the first PCs can indicate an increased level of comovement among firms. In turn, the degree of comovement determines the degree of fragility of the system and governs its resilience to shocks, with a possible interpretation of the degree of comovement in terms of the accumulation of systemic risk in the system. As stated by Aït-Sahalia and Xiu (2019), idiosyncratic factors become relatively less important and even more dominated by common factors during a crisis. Proper analysis of eigenvectors provided further insight in this direction, as it allowed the recovery of information about the role of single firms as potential sources of systemic risk in different periods of time.

3.2. Realized eigenvalues

Fig. 1 presents the percentage of the total variation, jointly explained by the first three components (top blue line) and the percentage individually explained for each component, the first in red, the second in yellow, and the third in violet. As in Ait-Sahalia and Xiu (2017), we see that the percentage of variance explained by the first PC (red) has fluctuated considerably during the period analyzed. Fig. 2 shows that the annual average of the percentage of total variation explained by the first three PCs for the entire period was around 40%. That percentage increased considerably in 2008, to 46%, with a peak in the week of LEH bankruptcy, September 15, 2008, of 65%. In 2016, we again found that the first three PCs explained up to 47% of the total variation, with a peak at 54% when the Brexit referendum occurred on June 22, 2016. Finally, in 2020, the first three PCs explained, on average, 50% of the total variation, reaching a peak of 66%, in the last week of February, the beginning of the COVID-19 pandemic. To shed some light on the

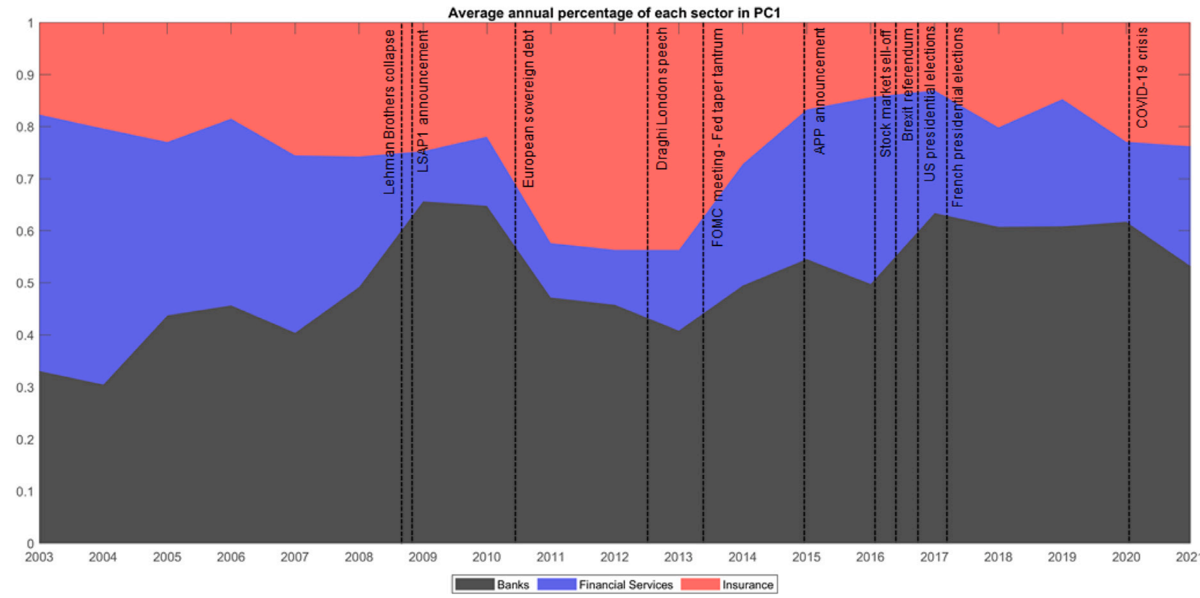

Fig. 3. Average annual percentage of each sector in PC1.

information content of stock prices, in Fig. 1, we highlight the weeks in which there are important events associated with both US and EU monetary policy announcements or other macro-events. Surprisingly, we found that large peaks in the variation explained by the first three PCs, indicating an increased level of comovement, which could be interpreted as an increase in financial stress, coincide with macro-, monetary- and global risk shocks,[8] further confirming the presence of market reactions to external shocks. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) found that greater interdependence in the banking and insurance sectors increased the likelihood that a large negative idiosyncratic shock could propagate through the financial system, affecting overall risk-taking behavior. Consequently, the observed peaks in the realized eigenvalues could be associated with periods in which the interbank market acted as an amplifier of idiosyncratic shocks, anticipating further financial distress. In general, these results emphasize that information extracted from the price of financial company stock through the realized eigenvalues can help policymakers and investors monitor the state of the market, while the possibility of forecasting periods of financial stress would reduce the cost of a financial crisis in the future.[9]

3.3. Realized eigenvectors

Nguyen, Tran, and Nguyen (2018) linked $\gamma_{1,i}$, the components of the eigenvector associated with the largest eigenvalue, to the degree of correlation ω_i of each firm, which is defined as:

$$\omega_i = \sum_{j=1, j\neq i}^{N} \rho_{ij}, \tag{6}$$

where ρ_{ij} is the correlation between the *i-th* and *j-th* companies. Therefore, we can interpret the company's eigenvector component as a measure of the correlation of that firm with the other companies included in the analysis. For example, if a firm has the largest component in the eigenvector (i.e., that firm has the largest loading to the first realized PC), it would be, on average, mostly correlated with others, having high chance of being highly systemic. By examining the eigenvectors, we can thus identify if each sector plays a major role in the correlations and might be a significant contributor to systemic behavior; in other words, the larger the sector component (the sum of the components associated with companies belonging to that sector), the stronger the influence of the sector.

Therefore, we studied the eigenvector associated with the largest eigenvalue to identify whether the behavior of the financial market is dominated by a sector. In this sense, Fig. 3 shows an area plot that represents the annual average of the first normalized integrated eigenvector by sector: banks (black), financial services (blue) and insurance firms (red). We can find three periods; (1) before the LEH bankruptcy in September 2008, the contribution from the bank sector increased, the contribution from the financial services sector decreased, and the contribution from the insurance sector appeared to be constant; (2) between the European sovereign debt crisis and the Federal Open Market Committee (FOMC) in June 2013, when it was stated that the Federal Reserve System (FED) would likely start slowing the pace of its bond purchases (commonly called the "taper tantrum") later in the year. During this period, the contribution of the bank sector decreased, the role of the financial services sector remained stable, and the role of the insurance sector drastically increased; and (3), during the last part of the sample, the contribution of the bank and financial services sectors increased and the insurance sector decreased until 2016 when the referendum on Brexit and the US presidential elections took place. During the COVID pandemic, the contribution of the banking

[8] List of events Date/Event/Type: 16 September 2008/Lehman Brothers Collapse/Global risk; 26 November 2008/Large-Scale Asset Purchase (LSAP1)/US monetary shock; 8 July 2010/Securities Markets Program announcement as a consequence of European Sovereign Debt Crisis initiated with the EU-IMF bailout for Greece/Euro Area (EA) monetary shock; 27 July 2012/Draghi London Speech:"Whatever it takes"/EA monetary shock; 20 June 2013/Federal Open Market Committee (FOMC) meeting - Fed taper tantrum/US monetary shock; 23 January 2015/ECB asset purchase programs (APP) announcement/EA monetary shock; 07 March 2016/APP expansion with carries a stock market sell-off/EA monetary shock; 27 June 2016/Brexit referendum/EA macro and global risk; 9 November 2016/US presidential elections/US macro and global risk; 25 April 2017/French presidential elections/EA macro and global risk; 25 February 2020/Intensification of COVID-19 crisis/Global risk.

[9] In this respect, a dynamic model for the prediction of realized eigenvalues and realized eigenvectors would be appropriate. We did not follow this research line, leaving it as a possible future research.

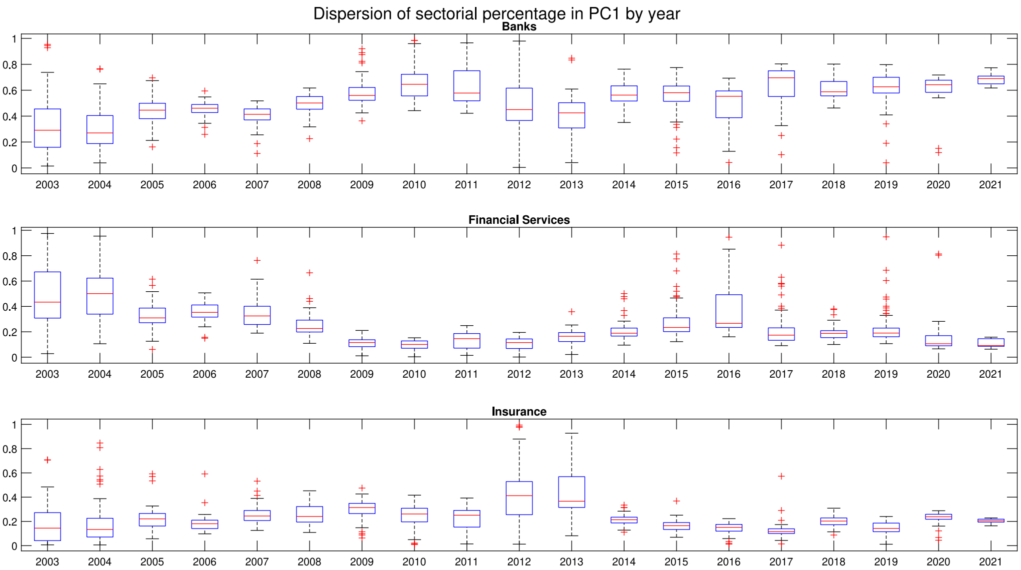

Fig. 4. Dispersion of sectorial percentage in PC1 by year.

sector decreased and that of the financial services and insurance sectors increased. In general, the contribution of banks is well above 50%, but for the period before 2008, in which financial services companies played a leading role and for a short period between 2011 and 2013 when insurance firms took the lead.

More in-depth analysis shows that between late 2003 and 2004, the financial services sector seemed to be the most systemic. In 2005, again, there was no main contributor to the first PC. Several triggering events of the Great Financial Crisis began with the bursting of the US housing bubble in 2005–2006, which increased the uncertainty of the financial markets in this period. However, from late 2006 to late 2007, the financial services sector seems to be the most systemic sector, according to its contribution to the first eigenvector. It turned out that in 2007, FNM and FRE, included in the financial services sector along with LEH, began to experience large losses in their retained portfolios, especially in their Alt-A[10] and subprime investments, thus becoming significant contributors to the general systemic risk. As we will see later when analyzing individual contributions, the weight of these three firms in the first PC increased steadily beginning in January 2008. The bank sector was the main contributor to the first component in late 2007, when it became apparent that the financial markets could not solve the subprime crisis and the interbank market that keeps money moving around the world froze completely, largely due to fear of the unknown. Northern Rock had to approach the Bank of England for emergency funding due to a liquidity problem. In October 2007, the Swiss bank UBS became the first major bank to announce losses, up to $3.4 billion, from subprime-related investments. It should be noted that before the LEH bankruptcy, the insurance sector seems to contribute the least to the first PC; contrary to the bank sector, the insurance sector has a much lower liquidity risk and maturity mismatch and is much less directly interconnected, which is why the insurance sector is not considered the main source of systemic risk. However, as we will see later when analyzing individual firms, AIG played a key role during the Global Financial Crisis, in which the three sectors showed a high level of connection.

The declining contribution of the financial services sector continued immediately after the LEH bankruptcy. In early 2009 (when the federal regulators had already put FNM and FRE into conservatorship, on September 6, 2008, and LEH had gone into bankruptcy on September 15, 2008), the bank sector's contribution became larger, increasing up to early 2010, when the insurance sector's contribution drastically increased. This last movement was started by the European sovereign debt crisis, initiated by the EU-IMF bailout for Greece, and lasted until late 2012, well after Draghi's "whatever it takes" statement. At this point, the average loading of the banking and financial services sectors started to increase their contribution to the first PC. The insurance sector weighed more than the other two sectors during the sovereign debt crisis (European sovereign debt and the "taper tantrum" of 2013 in the United States). The reasons for this apparently systemic behavior might be explained by the fact that government bonds, which are the largest and typically least risky part of insurers' investment portfolios, were the sources of instability and risk. This factor could have pushed the stress levels beyond the maximum risk tolerance of the insurers.

Overall, our analysis showed that the bank sector turned out to be the largest contributor to the first PC after the LEH bankruptcy, and the insurance sector might have had less systemic relevance than the other two sectors, but for the sovereign debt crisis starting in mid-2012. The business model and structure make the insurance sector a risk absorber rather than a risk contributor. For policymakers, insurance firms can generally be considered stable investors, except in periods of severe financial stress.

The richness of the HF PCA also allowed us to study the average contribution on a weekly basis. For each year, the box plots in Fig. 4 show the distribution of the weekly contribution to the first PC for each sector.[11] We can highlight several aspects. First, periods of severe crisis, such as 2008 (Great Financial Crisis) and 2020 (COVID-19 pandemic), showed high kurtosis, together with a concentration around the median. The positive skewness shown by the financial services sector in 2008 represents the large contribution of FRE, FNM, and LEH this year. Second, there is great variation in sector contributions during periods of milder crisis, such as in 2012–2013 (European sovereign debt and "taper tantrum" of 2013 in the US) and 2015–2017 (in January 2015, the ECB announced an expanded asset purchase program to address the risks of a too-prolonged period of low inflation that triggered a

[10] Classification of mortgages with a risk profile falling between prime and subprime.

[11] Each box displays the 25th, 50th (median), and 75th percentiles of the weekly contributions to the first PC during a year. Whiskers along with red + symbols (extreme contribution) provide accurate information about the behavior of the sector throughout the year.

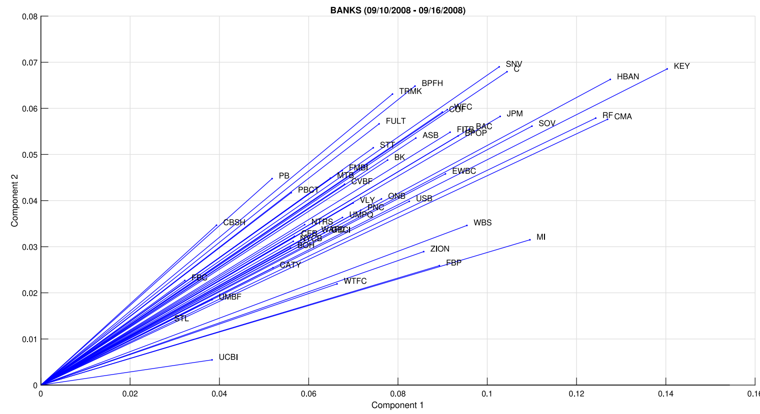

Fig. 5. Week 09/10/2008-09/16/2008. The first and second principal components (PCs) define the loading plot (LP) axes onto which the first and second eigenvectors are projected. The x_i and y_i coordinates of each point in the LP represent the *i-th* company loadings on the first and second PCs, the *i-th* element of the first and second eigenvectors. Each pair of coordinates is drawn as a vector connected to the origin. Large loadings (positive or negative) indicate that a particular company has a strong relationship with a particular PC. The sign of a loading indicates whether a variable and a PC are positively or negatively correlated. The top panel shows the biplot for the bank sector, the middle for the financial services sector, and the bottom for the insurance sector.

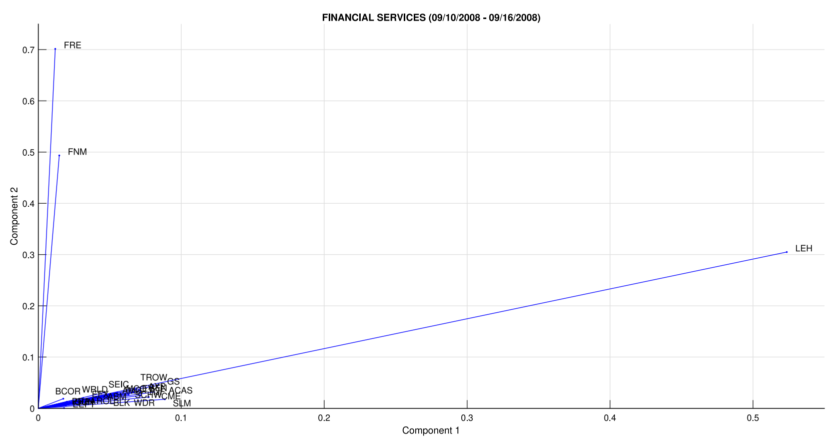

Fig. 6. Week 09/10/2008-09/16/2008. Financial Services. See Note in Fig. 5.

stock market sell-off; in June 2016 the Brexit referendum took place, and in November 2016, there was the US presidential election). It should be noted that in the period 2012–2013, the largest variation and contribution came from banks and insurance firms. In 2016–2017, the annual distribution of banks and financial services contributions to the first PC is not only widely spread out, but is also positively skewed for financial services and negatively skewed for banks. In general, the contribution of the bank sector was greater during these two years, though the financial services sector showed a stronger contribution during some weeks of that year. Finally, from 2009 to the end of the sample, except for the 2012–2013 period (European sovereign debt crisis), the insurance sector showed a stable contribution during the entire year, high kurtosis, and weak negative skewness.

Therefore, the study of weekly contributions by sectors to the main component is of great importance in understanding and tracking the complex behavior of the financial sector during different periods. Simple visual analysis has shown that the distribution of the eigenvector might have a good deal of information to follow up and anticipate financial turbulence.

The first eigenvector was the linear combination of assets that explained the largest fraction of the total risk of the assets. As shown, every company in our sample had a positive contribution to the first PC, according to the common interpretation of the first PC as a proxy for the market factor. Therefore, the first eigenvector indicated what the main contributors were for the market every week, which could be seen as the more systemic companies. The second eigenvector was a linear combination of assets orthogonal to the first eigenvector, which explained the greatest fraction of leftover asset variance, that is, the risk not yet explained by the first eigenvector. The contributions to the second PC are a little more interesting. On 16 September 2008, LEH Brothers went bankrupt, and, during this week, four companies stood out for their contribution to PC2: AIG, FRE, FNM, and LEH. This event showed that most of the firms in the dataset were highly integrated, but for these four, they tended to be segmented from other stocks because the factors that influenced the movement of these stocks during this week were dominated by internal factors rather than by the market.

To verify this interpretation, in the next section we will use a useful tool called a loading plot, which plots the contribution of the original variables to the first two components (Figs. 5–7).

4. Loading plots

Loading plots (LP) are linear projections of data in two-dimensional planes that attempt to preserve the intersection structure present in the original multidimensional space R^d. In an LP, the axes are usually represented by the first and second PCs, and each variable (a firm in our case) is represented by its contributions to the first two PCs. The contribution is recovered from the eigenvectors, and each pair of coordinates is drawn as a vector connected to the origin. Firms that have little contribution to a PC have almost zero weight in the associated loading. The sign of the coordinates indicates whether a variable and a PC are positively or negatively correlated. Strongly correlated companies will

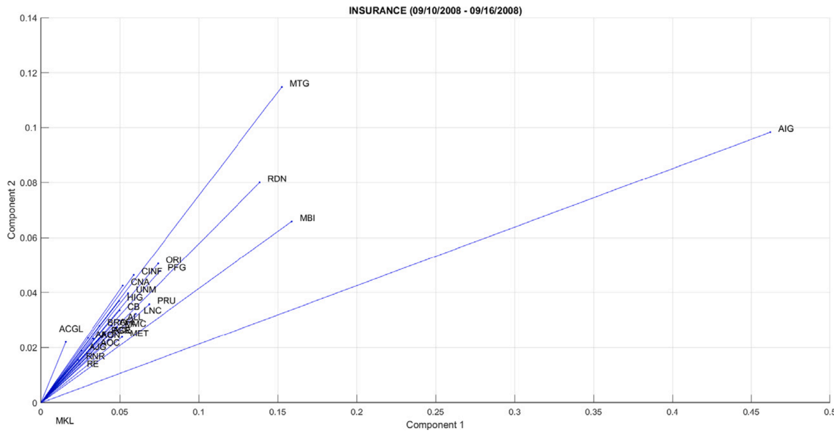

Fig. 7. Week 09/10/2008-09/16/2008. Insurance. See Note in Fig. 5.

have approximately the same vector direction. The length of the vectors approximates the variance of the corresponding firms.

LPs are a powerful tool for capturing several features of multivariate data and may be useful in systemic risk analysis, contributing to the prevention of financial distress. An appropriate diagnosis of systemic risk requires the evaluation of the structure of the financial system and the measurement of internal interconnection at each period of time. In this sense, LPs provide multivariate information between firms and the relationship between them, allowing us to quickly locate similar firms and investigate the cross-sectional structure of the market. Furthermore, the internal structure of the financial system varies over time and can itself be a major engine of financial instability. Compound imbalances over time increase the fragility of the system, which makes the procyclicality of agents, only detectable by observation over time, highly correlated with systemic risk. This time-varying dimension of systemic risk can be added to the LP projecting the contribution for consecutive weeks onto the first two PCs. When all the points are joined, the internal dynamics of the financial system can be followed.

4.1. Empirical loading plots

The two-dimensional projection LP display is based on the weekly integrated eigenvectors obtained following the Aït-Sahalia and Xiu's methodology explained in Section 2. LPs allow us to identify within-sector differences; for example, Figs. 5–7 show the components of the eigenvectors 1 and 2 estimated for week 09/10/2008-09/16/2008, in which the LEH bankruptcy occurred when the financial crisis entered a turbulent phase marked by failures of prominent American and European banks. Fig. 5 shows the LPs for banks, Fig. 6 for financial services, and Fig. 7 for insurance firms. These LPs show that contributions to PC1 were always positive.

According to Figs. 5–7, four firms stand out for their contributions to PC1 and/or PC2 and played a decisive role during the Great Financial Crisis in 2008: AIG, FRE, FNM and LEH. AIG (Insurers) and LEH reported a strong positive contribution to both components, and FRE and FNM showed a strong contribution to PC2. An in-depth analysis of the contributions of the companies to the first three PCs is shown in Fig. 8 through the factor loading of the first three eigenvectors. Companies are classified according to sectors. The first and second eigenvectors have only positive contributions. Apart from LEH, FNM, and FRE, belonging to the financial services sector, there were three insurance firms, MTG (Metlife), RDN (Radian Group) and MBI (MBIA), with a fairly high contribution to PC2. Not surprisingly, these three companies provide private mortgage insurance to protect lenders from default-related losses. These results show that during this tumultuous week, the second continuous PC tells us whether the company is closely linked to mortgage activities or not.

Figs. 5–7 also illustrate dissimilarities between the corresponding firms approximated by the Euclidean distance between two observations. Firms that are far away from each other have a high Euclidean distance, and vice versa. For example, in the middle panel (financial services), FRE and FNM were quite similar this week (the federal regulators had put FNM and FRE into conservatorship on September 6, 2008). Overall, these findings show that the HF PCA really does a good job summarizing the information in the 100-company dataset and gives us a lot of information about the behavior of the system.

The internal structure of the financial system changes over time and can itself be a major engine of financial instability. We can also use LPs to identify intersectoral differences that vary over time. Figs. 9 and 10 show the path followed by the median company of each sector in relation to the first two PCs in 2008 and 2020, respectively.[12] Each LP point represents the median contributions to PC1 and PC2 of firms that belong to banks (left panel), financial services (middle panel), and insurance firms (right panel) at time *t*. Every point is joined in the right order. In Fig. 9, we have highlighted three weeks using a dashed vector for the week of the LEH bankruptcy and a thick black vector for the first and last week of the year (clockwise from the top left, 12/24/2008 and 01/07/2008). This plot illustrates that the dynamic behavior of the median banks, financial services, and insurance firms showed similar time-varying behavior, and it seems that there are no notable intersectoral differences. The median company has erratic trajectories in a cloud close to PC1; in this cloud, companies lie most of the weeks of the year, but there is strong anticlockwise movement in September along with the first week of July (on July 13 the US Treasury and Federal Reserve effectively nationalize FNM and FRE) and last week of the year. As seen above during the turbulent week of the LEH bankruptcy, the median company's contribution to PC2 increased.

Fig. 10 shows the trajectories followed by the median firms for each sector in 2020. In this plot, two weeks are highlighted using a thick black vector for the first and last weeks of the year (clockwise from the top left, 01/06/2020, and 12/24/2020). Unlike 2008, early 2020 bears little resemblance to the rest of the year. The dynamic LP exhibits a clockwise arc trajectory starting in January and February, showing that the second PC, though responsible for the dynamic behavior during those months, played a minor role during the rest of the year. The median bank seems to contribute more (length of the vectors) to the first two PCs than the other two median companies. An in-depth analysis of the graph shows that at the outbreak of the COVID-19 pandemic in March 2020, while the median company in each sector showed a large contribution to the first PC (vectors are parallel to

[12] We thank J. Egido for providing the code for computing dynamic LPs. See Egido and Galindo (2015).

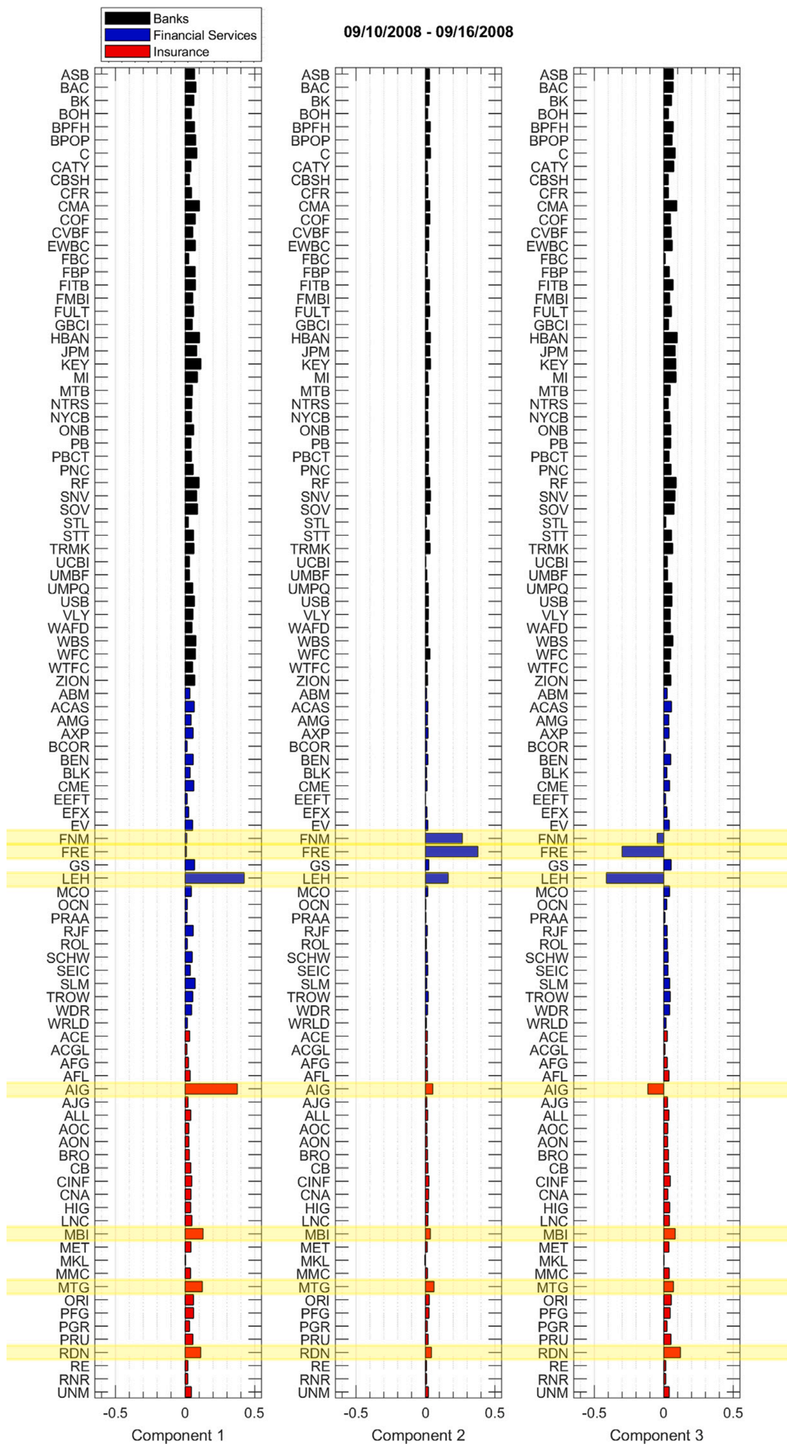

Fig. 8. Loadings of the first three PCs (week of LEH bankruptcy).

the horizontal axis), their contributions to the second PC were small, reaching a negative value in the first three weeks of March for the median average in financial services and insurance firms. The change in the contribution from January 2020 to March 2020 is especially significant; the trajectory drastically shifted towards PC1. The cosine of the angles between the markers and the axes (PCs) also approximates the correlation between the two states. Therefore, the cosine of the angle near 90° between the position at the beginning of the year and the one in March approximates the low correlation between the two states of the company. If PC1 were associated with an equally weighted market portfolio, the position in March of the average company for the three sectors in March shows how these sectors followed the market. Caporin et al. (2021) found that the entire financial sector did not turn out to be a systemic sector during this crisis.[13]

[13] Although not reported, provided upon request, the projection onto the first two PCs of the contribution for consecutive weeks of any individual company reveals interesting issues about the behavior and the role played by these companies during turbulent periods. For example, during high-volatility periods, long-length markers and drastic shifts in the cosine of the angle with the PC1 were observed. During calm periods, long-length markers were also

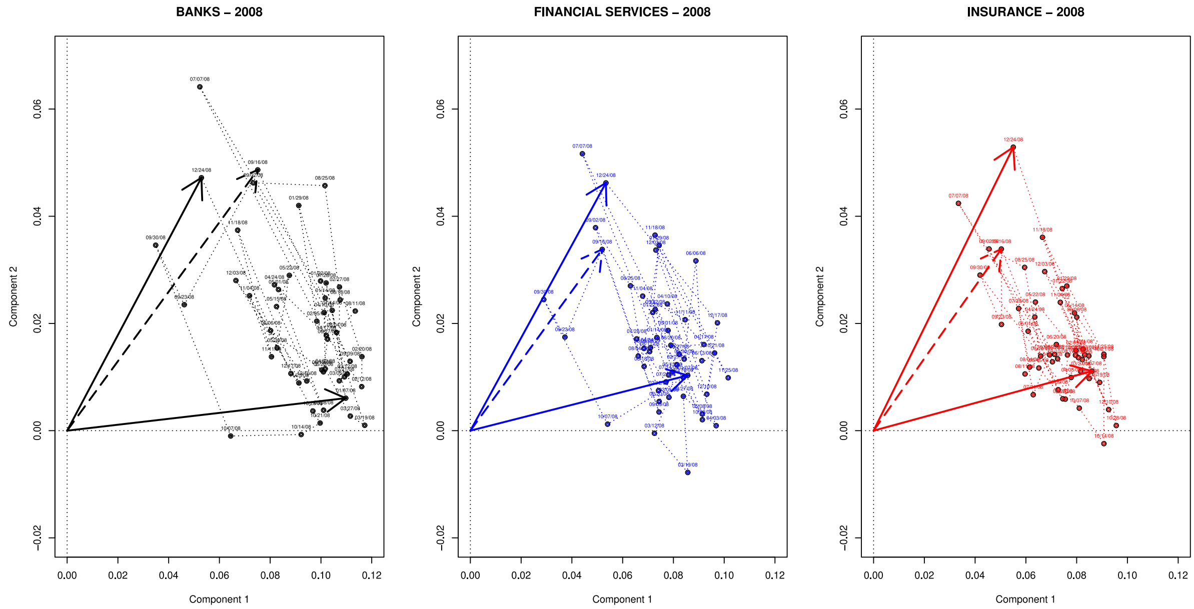

Fig. 9. Dynamic LPs: trajectories followed by the median firm for each sector in 2008. Every biplot point represents the median of the contributions to PC1 and PC2 of the firms that belong to banks (left plot), financial services (middle plot), and insurance firms (right plot) at time *t*. Every point is joined in the right order. Three weeks are highlighted using a dashed vector for the week of LEH bankruptcy (09/16/08) and two thick black vectors for the first and last week of the year (clockwise from the top left, 24/12/08 and 01/07/08).

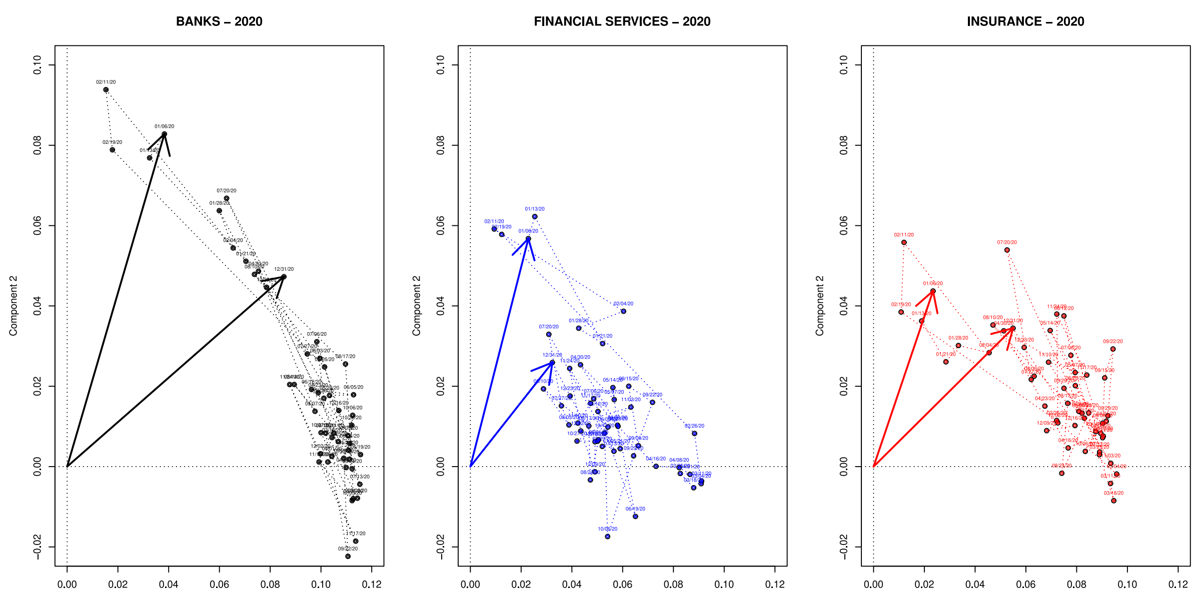

Fig. 10. Dynamic LPs: trajectories followed by median firms for each sector in 2020. Every LP's point represents the median of the contributions to PC1 and PC2 of the firms that belong to banks (left plot), financial services (middle plot), and insurance firms (right plot) at time *t*. Every point is joined in the right order. Two weeks are highlighted using a thick black vector for the first and last week of the year (clockwise from the top left, 01/06/20 and 12/31/20).

It is already clear that financial crises always have key differences, and paying attention to them helps to better understand the current state of the market and to make predictions about its future development. LPs allow us to draw out some lessons from the specific structure and interconnection existing at different times between the three sectors we analyzed. To do so, we focus on the median of contributions to the first two PCs of companies belonging to the three sectors. We point attention to those weeks in which there were important events associated, for instance, with announcements of monetary policy of both the US and the EU, or other macro events (see footnote 5); we provided a graphical representation of the medians in Fig. 11. Regarding the sector contribution to the first and second PCs, LPs provide an intuitive way to investigate how similar the different weeks of the sample are. LPs convey information about the correlation among sectors and, by using them dynamically, we can display several elements concisely but accurately: changes in location, variation, and correlation structure of the multivariate process data. For example, Fig. 11 shows that LEH collapse in September 2008 (circles in black ellipsis) was different from

observed, however, no drastic changes were found in the correlation with PC1. Therefore, these two dimensions, the high volatility of the company and the drastic changes in correlation with PC1 and PC2 can be early warnings of critical changes in the state of a company.

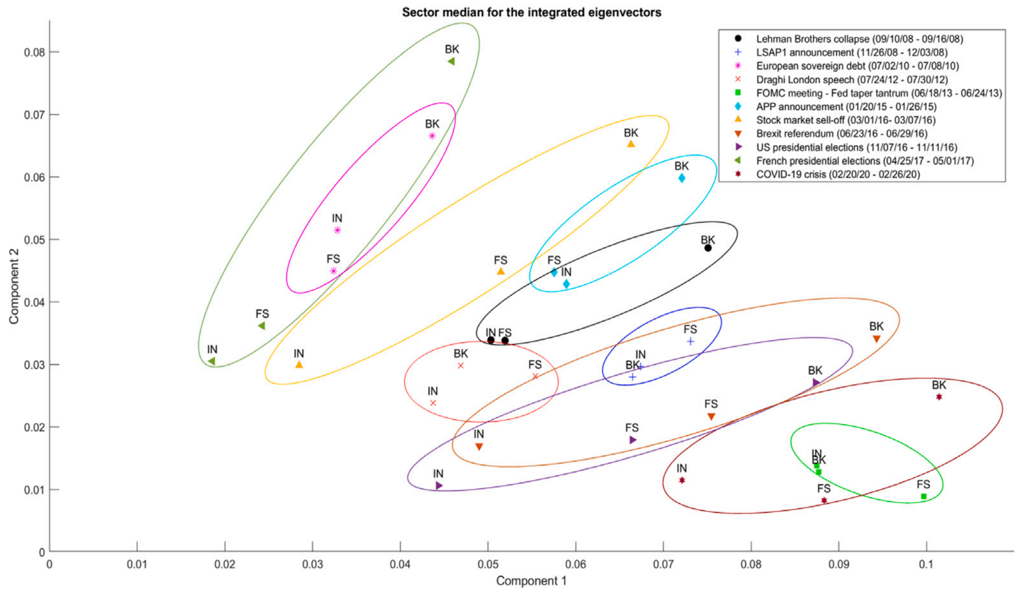

Fig. 11. Loading Plot: The axes are represented by the first and second PCs and each sector is represented by the median of the contributions to the first two PCs, given by the eigenvectors that are projected perpendicularly onto the axes. Every ellipsis refers to each week in which one of the events described in footnote 6 is produced.

the COVID-19 outbreak in March 2020 (hexagrams in red ellipsis). The contribution to PC2 was higher during the LEH bankruptcy than during the COVID-19 outbreak, somewhat closer to late January 2015 (diamonds in blue ellipsis), when the ECB announced an expanded asset purchase programs to address the risks of a too-prolonged period of low inflation that triggers a stock market sell-off. It should be noted that while PC1 can be roughly associated with an equally weighted market portfolio, as already confirmed in many studies, identifying PC2 is challenging, but it could be related to an index tracking the entire financial market that deviates from the entire market during turbulent periods. Therefore, the three financial sectors appear to have had a particularly higher deviation from the full stock market in 2008 than in 2020. Furthermore, during the LEH bankruptcy, the three sectors appear to cluster as the angle between them is close to zero, indicating a high level of correlation, which can be interpreted as the three sectors being globally connected. The first and second PCs appear to have had a particularly higher contribution from the median bank company. It is interesting to note that the behavior of the financial system in response to different shocks, endogenous in 2008 and exogenous in 2020, is very distinct.

Summarizing our findings, we can state that dynamic LPs updated weekly would allow policymakers to continuously monitor the market structure in almost real-time and permit the design of a better strategy to identify systemic states. Beyond understanding the financial market structure, policymakers are also interested in identifying the mechanisms through which the rich set of information contained in the stock prices of financial companies propagates to other markets, helping predict future financial instability. In this sense, the next section, built upon the HF data used so far, will search for signals on the market structure underlying the dynamics of the financial sector's stress condition and analyze the transmission to other sectors of the economy, as summarized by market-wide stress indexes. In particular, we will link realized eigenvalues to different systemic stress indexes by resorting to the approach put forward by Diebold and Yilmaz (2012).

5. Measuring spillover effects

Monetary policymakers closely monitor fluctuations in stock prices to seek signals on the underlying expected dynamics of the economy. It is well established that stock prices contain a rich set of information that propagates to other markets, but it is less understood whether the information embedded in the comovement among stock prices could help predict future financial instability and crisis. The dot-com crisis, the widespread effects of the Global Financial Crisis, and the recent significant impact of the COVID-19 pandemic renewed and fueled interest in the measurement of financial stress[14] that, although not directly observable, manifests itself through increased uncertainty and changes in expectations about the future of market participants. Both aspects are reflected in the price of the shares. According to past empirical evidence, severe financial stress is preceded by increased market volatility, and the mechanisms through which volatility spills over across economic sectors have important implications for investors, regulators, and policymakers. This could also lead to the introduction of regulatory and institutional rules to reduce the cross-market impact of excessive price movements (Laborda and Olmo, 2021).

Motivated by such consideration, this section aims to offer an HF-based assessment of the financial sector's stress condition. Furthermore, we analyzed the interdependence and spillover mechanism between HF eigenvalues and other summary measures of financial stress. There have been many attempts to measure financial stress and its spillover effects, but to our knowledge, none of them have used HF eigenvalues. The availability of HF data provides policymakers with the opportunity to analyze short periods of time and identify with much less statistical uncertainty the real-time reactions of stock prices to economic news; market participants quickly react after a change in expectations that could refer, for instance, to economic growth or inflation levels.

Following the methodology introduced by Diebold and Yilmaz (2012) which is described in Section 2.2 briefly, we studied the transmission of shocks from (to) stocks of the financial sector to (from) other non-financial sectors and the real economy. We use the first realized eigenvalue as a measure of the information content of the HF PCs. The size of the eigenvalue is informative both in absolute terms and relative to the entire collection of realized eigenvalues. This strategy builds on the well-stated fact that the first PC shows a strong resemblance to the market index. The idea that the first PC is close to the index has been around for some time. Aït-Sahalia and Xiu (2019) and Pelger (2019),

[14] Financial stress is defined as a 'mix of market conditions, in which market participants experience increased uncertainty or change their expectations about future financial losses, the fundamental value of assets, and economic activity' (Kliesen, Owyang, and Vermann, 2012).

using HF data of assets included in the S&P 500 Index, estimated four factors and concluded that the first statistical factor appears to be an equally weighted market portfolio. In this sense, the first eigenvalue is a proxy for the level of volatility (risk) of the market and, therefore, a proxy for the level of financial stress. Additionally, the first eigenvalue reflects changes in the average correlation between stocks, making the first eigenvalue a reliable high-frequency tool to measure systemic stress. Plerou et al. (2002) supported the idea that during periods of high volatility when the correlations among assets are increased, the largest eigenvalue and its eigenvector reflect the collective response of the entire market to shocks such as certain news breaks (e.g., central bank interest rate hikes). Coronnello, Tumminello, Lillo, Micciche, and Mantegna (2005) using five-minute data found that the largest eigenvalue describes the common behavior of the stocks composing the LSE stock index. The higher the eigenvalue in absolute terms, the large the variance of the first PC and, in general, the higher the overall risk in the system. The higher the eigenvalue in relative terms, the greater the interconnectivity between firms, which determines the degree of fragility of the system and governs its resilience to shocks. These elements lead to a relevant interpretation in terms of the accumulation of financial stress in the financial market. The system we considered for our analyses includes one of the first three realized eigenvalues and four additional indices commonly used as measures of market volatility, systemic stress, and policy uncertainty: (i) the VIX volatility index, or 'fear index', introduced by the Chicago Board Options Exchange, which measures the market expectation of 30-day forward-looking volatility implied by at-the-money S&P 500 index options, (ii) the St. Louis Fed Financial Stress Index (SLFSI), which measures the degree of financial stress in the markets and is constructed from 18 weekly data series, all of which are weekly averages of daily data series: seven interest rates, six yield spreads, and five other indicators, developed by the Federal Reserve Bank of St. Louis (see Kliesen and Smith, Kliesen and Smith, for more details), (iii) the Economic Policy Uncertainty Index (EPU) based on newspapers in the United States, also developed by the Federal Reserve Bank of St. Louis (see Baker, Bloom, and Davis (2016), for additional details), and (iv) the TrAffic LIght System for Systemic Stress $TALIS^3$ (TALIS), developed by Caporin et al. (2021, 2022), which combines the information contained in the $\Delta CoVaR$ and the financial institutions/sector shortfalls (the realized losses of an financial institution/sector are larger than the expected VaR).

Although VIX captures the uncertainty of the equity market, covering publicly traded firms that account for about one-third of private employment, the EPU index reflects policy uncertainty, not just referring to equity returns. The EPU measures the uncertainty about US fiscal, regulatory, and monetary policies that could have a large impact on economic decline and recovery. According to Baker et al. (2016), an increase in policy uncertainty increases stock price volatility, lowers investment rate, and employment growth rates in government-exposed sectors (defense, healthcare, and construction), and therefore could have a severe impact on aggregate investment, employment, and output. Regarding the SLFSI index, it captures a broad perspective of financial stress in the market as a whole, including both the stock and bond markets. Finally, $TALIS^3$ provides a measure of systemic stress.

We will thus exploit the information content of HF comovements in equity prices and show that the information extracted from the HF comovement at stock prices is carried over to policy- and financial-uncertainty indicators.

Table 2 shows the volatility spillovers across the first eigenvalue (EIGV1)[15] and the four macro-financial variables, that is, VIX, SLFSI, EPU, and TALIS for the entire sample period. Each entry ij is the estimated contribution to the variance of the forecast error of variable i originating from variable j. The row labeled 'To Others' is the off-diagonal column sum and represents the directional volatility spillover transmitted by the variable i to all other variables j. The column labeled 'From Others' is the off-diagonal row sum and represents the directional volatility spillovers received by the variable i from all other variables j. The row labeled 'NET' is the difference between the gross volatility shocks transmitted to and those received from all other variables. Furthermore, the total spillover index appears in the bottom right corner of Table 2, which represents the average percentage of the variance of the forecast error of the five variables resulting from spillovers. It can be calculated as the average value of the row 'To Others' or as the average value of the column 'From Others'.

Table 2
Volatility spillovers across the first eigenvalue (EIGV1) and the macro-financial variables for the full sample period.

	EIGV1	VIX	SLFSI	EPU	TALIS	*From Others*
EIGV1	57.137	31.855	1.895	1.585	7.528	42.863
VIX	13.994	67.080	0.878	1.590	16.458	32.920
SLFSI	10.955	10.173	75.307	1.252	2.313	24.693
EPU	4.631	4.998	0.018	88.604	1.749	11.396
TALIS	6.766	22.874	0.232	0.005	70.123	29.877
To others	36.345	69.900	3.023	4.433	28.047	*Total Spillover Index*
Net	−6.518	36.981	−21.670	−6.963	−1.829	**28.350**

The main diagonal of Table 2 shows that more than 50% of the forecast error variance is self-explanatory for each variable. According to the row 'To Others', shocks to the VIX largely spillover across other indices (70%), in particular, the contribution to the volatility of the EIGV1 forecast error was relatively large (32%) well above the contribution to other indices as TALIS (23%), SLFSI (10%) and EPU (5%). Shocks to EIGV1 ranked as the second contributor to the variance of forecast errors of other indices (36%). Regarding the column 'From Others' the volatility spillovers from others to EIGV1 were the largest (42%), followed by VIX (33%) and TALIS (30%). Regarding the net effect, in the bottom row of Table 2, the largest was from VIX to others (70–33 = 37%) and from others to SLFSI (25–3 = 22%). It should be noted that the net directional volatility spillovers from EIGV1 to SLFSI (8%) and EPU (3%) were similar to that of VIX for both indices. The net effect from the other to EIGV1 was 7%, similar to the EPU from the other net effect. Surprisingly, the total volatility spillover index was 28%, which illustrates that, on average, the volatility of the forecast error for the five indices came from spillovers. To put our results into perspective, DY, analyzing the volatility data of the stock, bond, exchange rate, and commodity market, found that the total spillover index of volatility was equal to 13%. Our results indicate that the total and directional spillovers over our sample are fairly large.

Although Table 2 provides a useful summary of the average volatility spillovers, a further extension to include the dynamic interaction among the variables provides a much richer view. Fig. 12 addresses this problem by reporting the dynamic net pairwise spillovers calculated using a 200-week rolling window (approximately 4 years). Net pairwise spillover between EIGV1 and other indices was the difference between volatility spillovers from EIGV1 to another index and those transmitted from another index to EIGV1. Therefore, a positive (negative) net pairwise spillover indicates that the volatility spillover from EIGV1 to the other asset is greater (lower) than the one to EIGV1 from the other asset.

The upper left panel in Fig. 12 shows the net volatility spillover from EIGV1 to VIX. Although very negative, above 15% in 2008, reaching values greater than 25% between 2015 and 2019, the transmission of volatility shows a time-varying pattern during the full period. This result illustrates that the VIX was a net trigger of volatility, with financial markets being net volatility receivers. The forward-looking

[15] We used the square root of the realized eigenvalues to make the variation more uniform and of similar size to the other macro-financial variables. This is consistent with the interpretation of realized eigenvalues as variances of realized PCs. Therefore, the square root of the realized eigenvalues has a scale comparable to volatility.

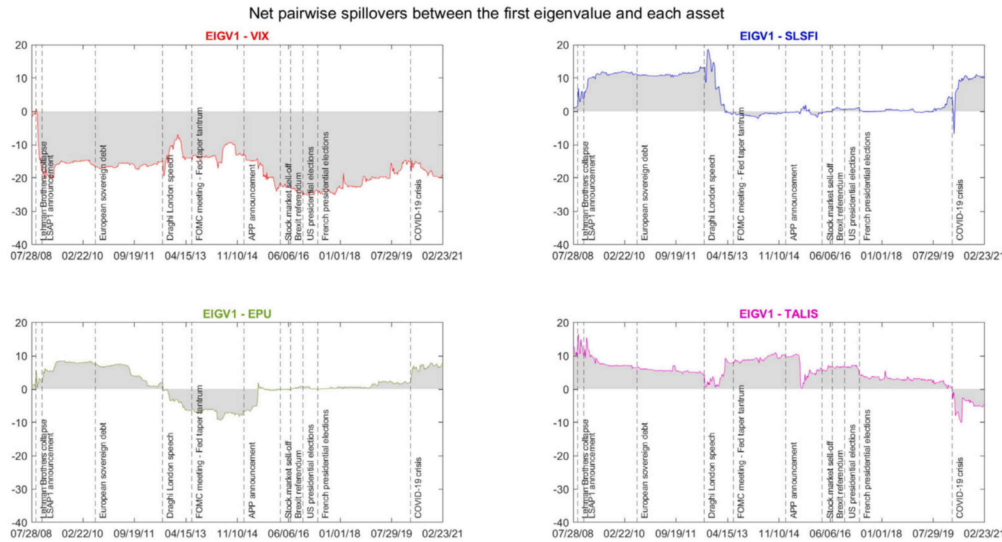

Fig. 12. Net pairwise spillovers between the square root of EIGV1 and VIX (top left panel), SLFSI (top right panel), EPU (bottom left panel), and TALIS (bottom right panel).

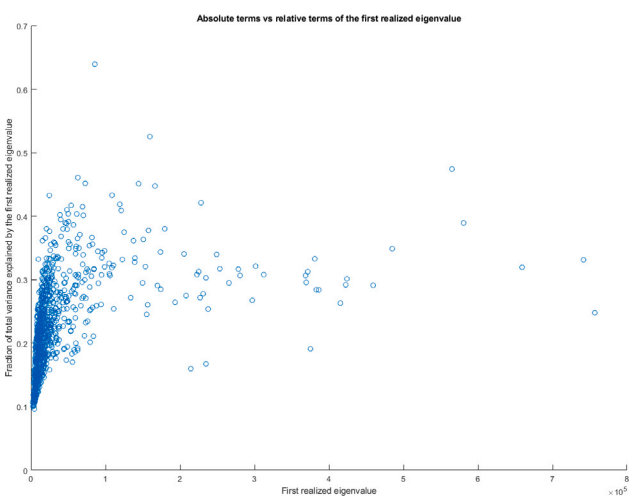

Fig. 13. First eigenvalue vs % of variance explained by the first eigenvalue.

characteristics of VIX make it superior to information content over other measures of volatility, such as EIGV1 based on historical information. The top right panel shows that the EIGV1 was a net transmitter to the SLFSI from mid-2008 to June 2013 (FED tapper tantrum). Apart from the Great Financial Crisis, from May 2010 there is high stress in financial markets because of the European sovereign debt crisis, whose impact decreased after Draghi's London speech in July 2012. During this period, the world stock exchange stumbled on fears of contagion of the European sovereign debt crisis, and the credit rating was downgraded because of the debt ceiling crisis in the United States. From mid-2013, the net volatility spillovers for the two indices were very low, close to zero, until the outbreak of COVID-19, when financial sectors again became volatility transmitters.

The bottom left panel in Fig. 12 shows a pattern similar to the previous subplot, but we observed a negative net pairwise spillover around 2012 and 2014, that is, the volatility spillovers from EPU to EIGV1 were greater than those from EIGV1 to EPU. Although Fig. 1 shows that from Draghi's speech in July 2012 to late 2015, uncertainty in the financial markets seems to be relatively lower, several developments in Europe and the United States kept EPU largely fluctuating around high levels during this period, namely sovereign debt and banking crisis in the Eurozone (rescue package for Portugal in May 2012, bailout package for Greece in July 2011, large yield increase on Spanish and Italian government bonds, etc.), intense battles over fiscal and healthcare policies in the US (debt-ceiling fight in summer 2011, uncertainties surrounding the US healthcare policy from August 2011 to June 2012). Russia's annexation of Crimea in 2014 also led to international sanctions that increased the level of global uncertainty. It should be noted that financial sectors seem to be transmitters of volatility during periods of high financial stress, as was the case in the GFC. These results shed new light on the literature that analyzes the relationship between EPU and stock price risk, with EPU impacting in a systematic way on equity risk, as stated by Luo and Zhang (2020) and Pástor and Veronesi (2013).

Finally, the bottom right panel of Fig. 12 shows TALIS as a net receiver of the volatility from EIGV1 until the outset of the COVID-19 pandemic in March 2020 when TALIS became a propagator of volatility. This behavior could be explained by the secondary role played by banks, financial services, and insurance firms as systemic sectors in the aftermath of the COVID-19 shock that hit a more resilient global financial system, which has changed over the past decade as a result of a wide set of monetary, fiscal, regulatory, and supervisory measures put in place following the 2008 financial crisis. TALIS, which is based on the full stock market, reported that market stress in March 2020 was mainly driven by sectors other than the banking, financial services, and insurance sectors. During the first months of 2020, economies faced an unprecedented economic lockdown. Full stock markets around the world experienced sharp drops that were comparable only to those during the outbreak of the Global Financial Crisis (GFC) in October 2008. During the COVID-19 pandemic, global systemic risk indices showed values even higher than during the GFC.

In Appendix B we show the previous volatility spillover analysis changing EIGV1 to EIGV2 and EIGV3 in the 4-variable system. A similar pattern is observed in Tables B.1 and B.2, showing the unconditional full sample measure of volatility spillovers among the four indices and EIVG2 and EIGV3, respectively. Volatility spillovers from/to the two eigenvalues and the total spillover index (26% for EIGV2) are slightly lower than when EIGV1 was included (28%). Again, results suggest that VIX is a high net trigger of volatility, for example, when EIVG2 is included, the impact To others is 66% with EIGV2 (27%), SLFSI (10%), EPU (5%), and TALIS (24%) being net receivers.

Regarding the net pairwise spillovers, Figs. B.1 and B.2 in Appendix B show the net volatility spillovers from the second and third eigenvalues to other indices. It should be noted that, as shown in the upper left panel of Fig. B.1, EIGV2 is a net volatility propagator

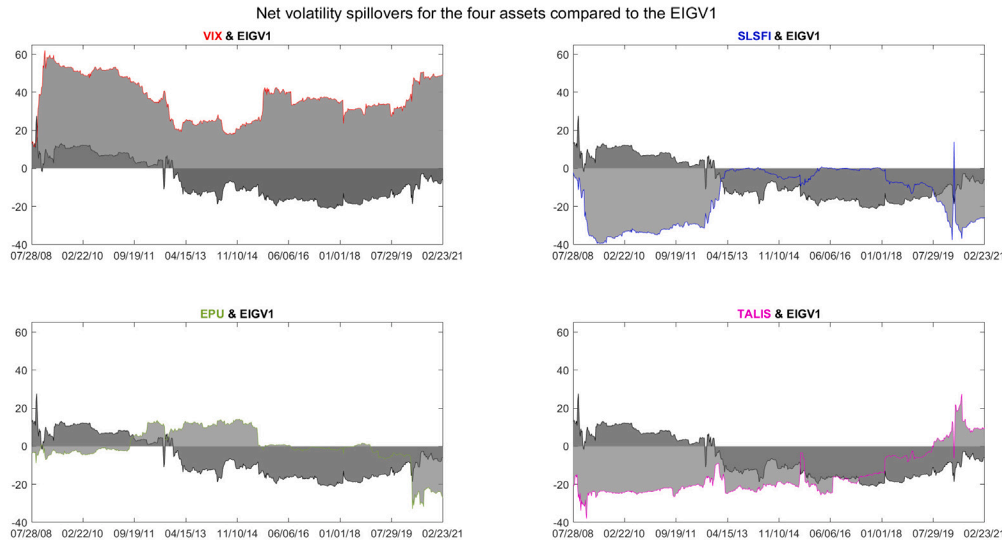

Fig. 14. Net volatility spillovers for the four assets and the square root of the first eigenvalue (EIGV1).

Table A.1
Names and classification of 101 US financial institutions. In bold, 8 US financial institutions that are only analyzed in the period before Lehman Brothers bankruptcy (January 10, 2003–September 16, 2008).

47	Banks						
	MNEM	NAME	IND		MNEM	NAME	IND
1	ASB	Associated Banc-Corp	MB	25	MTB	M&T Bank Corporation	MB
2	BAC	Bank of America Corporation	MB	26	NTRS	Northern Trust Corporation	MB
3	BK	Bank Of New York Mellon Corporation (The)	MB	27	NYCB	New York Community Bancorp, Inc.	BA
4	BOH	Bank of Hawaii Corporation	MB	28	ONB	Old National Bancorp	MB
5	BPFH	Boston Private Financial Holdings, Inc.	MB	29	PB	Prosperity Bancshares, Inc.	MB
6	BPOP	Popular, Inc.	MB	30	PBCT	People's United Financial, Inc.	BA
7	C	Citigroup Inc.	MB	31	PNC	PNC Financial Services Group, Inc. (The)	MB
8	CATY	Cathay General Bancorp	MB	32	RF	Regions Financial Corporation	MB
9	CBSH	Commerce Bancshares, Inc.	MB	33	SNV	Synovus Financial Corp.	MB
10	CFR	Cullen/Frost Bankers, Inc.	MB	34	SOV	Sovereign Bancorp	BA
11	CMA	Comerica Incorporated	MB	35	STL	Sterling Bancorp	MB
12	COF	Capital One Financial Corporation	MB	36	STT	State Street Corporation	MB
13	CVBF	CVB Financial Corporation	MB	37	TRMK	Trustmark Corporation	MB
14	EWBC	East West Bancorp, Inc.	MB	38	UCBI	United Community Banks, Inc.	MB
15	FBC	Flagstar Bancorp, Inc.	BA	39	UMBF	UMB Financial Corporation	MB
16	FBP	First BanCorp.	MB	40	UMPQ	Umpqua Holdings Corporation	BA
17	FITB	Fifth Third Bancorp	MB	41	USB	U.S. Bancorp	MB
18	FMBI	First Midwest Bancorp, Inc.	MB	42	VLY	Valley National Bancorp	MB
19	FULT	Fulton Financial Corporation	MB	43	WAFD	Washington Federal, Inc.	MB
20	GBCI	Glacier Bancorp, Inc.	MB	44	WBS	Webster Financial Corporation	MB
21	HBAN	Huntington Bancshares Incorporated	MB	45	WFC	Wells Fargo & Company	MB
22	JPM	J P Morgan Chase & Co	MB	46	WTFC	Wintrust Financial Corporation	MB
23	KEY	KeyCorp	MB	47	ZION	Zions Bancorporation N.A.	MB
24	MI	Marshall & Ilsley Corp	BA				

Note: The abbreviations for the industry (IND) classification are as follows: BA = Banks, MB = Major Banks, AM = Asset Management, CF = Consumer Finance, IS = Investment Bankers/Brokers/Service, SF = Specialty Finance, AH = Accident and Health Insurance, IB = Insurance Brokers, LI = Life Insurance, PC = Property and Casualty Insurance, SI = Specialty Insurers.

during July–August 2008. As seen in the previous section, several companies (LEH, FNM, FRE, MTG, RDN, and MBI) closely linked to mortgage activities contributed largely to the second PC, which could be approximated by a portfolio of companies belonging to the bank, financial services, and insurance sectors facing a large exposure to the real state market. We did not find any similar behavior for the other two eigenvalues. After that short period of time, VIX again became a net volatility spillover transmitter. TALIS turned out to be a volatility spillover transmitter during the COVID-19 pandemic for the three eigenvalues.

In summary, our results suggest that there is a flow of volatility to the three sectors, banks, financial services, and insurance firms, from VIX. The volatility of PCs spread over to SLFSI and EPU with high intensity during the GFC and the COVID-19 pandemic. TALIS was a net transmitter of volatility to the three financial sectors during the COVID-19 pandemic. But for the short period in 2008, no differences were found in the graph of the volatility flow to and from the three eigenvalues. Although the second and third eigenvalues determine portfolios as less risky than the one defined by the first eigenvalue, it seems that the three eigenvalues contained similar information in terms of risk. These results show that the dimension of the impact of the shock of volatility to and from the first three eigenvalues might be stable for the whole sample. However, when we analyzed the percentage of variance explained by the first PC, we found that when the volatility of this factor was locally greater, it explained a higher portion of the correlation (variance) in the data. Fig. 13 shows the scatter plot of EIGV1 and the percentage of variance explained by it. The percentage of variance explained for the first PC increased with its size. Volatility

Table A.2
Names and classification of 101 US financial institutions. In bold, 8 US financial institutions that are only analyzed in the period before Lehman Brothers' bankruptcy (January 10, 2003–September 16, 2008).

26	Financial Services			28	Insurers		
	MNEM	NAME	IND		MNEM	NAME	IND
1	ABM	ABM Industries Incorporated	CF	1	ACE	Ace Limited Common Stock	PC
2	ACAS	American Capital, Ltd.	AM	2	ACGL	Arch Capital Group Ltd.	PC
3	AMG	Affiliated Managers Group, Inc.	AM	3	AFG	American Financial Group, Inc.	PC
4	AXP	American Express Company	CF	4	AFL	Aflac Incorporated	AH
5	BCOR	Blucora, Inc.	CF	5	AIG	American International Group, Inc.	PC
6	BEN	Franklin Resources, Inc.	AM	6	AJG	Arthur J. Gallagher & Co.	SI
7	BLK	BlackRock, Inc.	IS	7	ALL	Allstate Corporation (The)	PC
8	CME	CME Group Inc.	IS	8	AOC	Aon Corp	IB
9	EEFT	Euronet Worldwide, Inc.	IS	9	AON	Aon plc	SI
10	EFX	Equifax, Inc.	CF	10	BRO	Brown & Brown, Inc.	SI
11	EV	Eaton Vance Corporation	AM	11	CB	Chubb Limited	PC
12	FNM	Federal National Mortgage Association Fannie Mae	SF	12	CINF	Cincinnati Financial Corporation	PC
13	FRE	Federal Home Loan Mortgage Corp	SF	13	CNA	CNA Financial Corporation	PC
14	GS	Goldman Sachs Group, Inc. (The)	IS	14	HIG	Hartford Financial Services Group, Inc. (The)	PC
15	LEH	Lehman Brothers Holdings Inc	IS	15	LNC	Lincoln National Corporation	LI
16	MCO	Moody's Corporation	CF	16	MBI	MBIA, Inc.	PC
17	OCN	Ocwen Financial Corporation	CF	17	MET	MetLife, Inc.	LI
18	PRAA	PRA Group, Inc.	CF	18	MKL	Markel Corporation	PC
19	RJF	Raymond James Financial, Inc	IS	19	MMC	Marsh & McLennan Companies, Inc.	SI
20	ROL	Rollins, Inc.	CF	20	MTG	MGIC Investment Corporation	PC
21	SCHW	The Charles Schwab Corporation	IS	21	ORI	Old Republic International Corporation	PC
22	SEIC	SEI Investments Company	IS	22	PFG	Principal Financial Group Inc	AH
23	SLM	SLM Corporation	CF	23	PGR	Progressive Corporation (The)	PC
24	TROW	T. Rowe Price Group, Inc.	IS	24	PRU	Prudential Financial, Inc.	LI
25	WDR	Waddell & Reed Financial, Inc.	IS	25	RDN	Radian Group Inc.	PC
26	WRLD	World Acceptance Corporation	CF	26	RE	Everest Re Group, Ltd.	PC
				27	RNR	RenaissanceRe Holdings Ltd.	PC
				28	UNM	Unum Group	AH

Note: The abbreviations for the industry (IND) classification are as follows: BA = Banks, MB = Major Banks, AM = Asset Management, CF = Consumer Finance, IS = Investment Bankers/Brokers/Service, SF = Specialty Finance, AH = Accident and Health Insurance, IB = Insurance Brokers, LI = Life Insurance, PC = Property and Casualty Insurance, SI = Specialty Insurers.

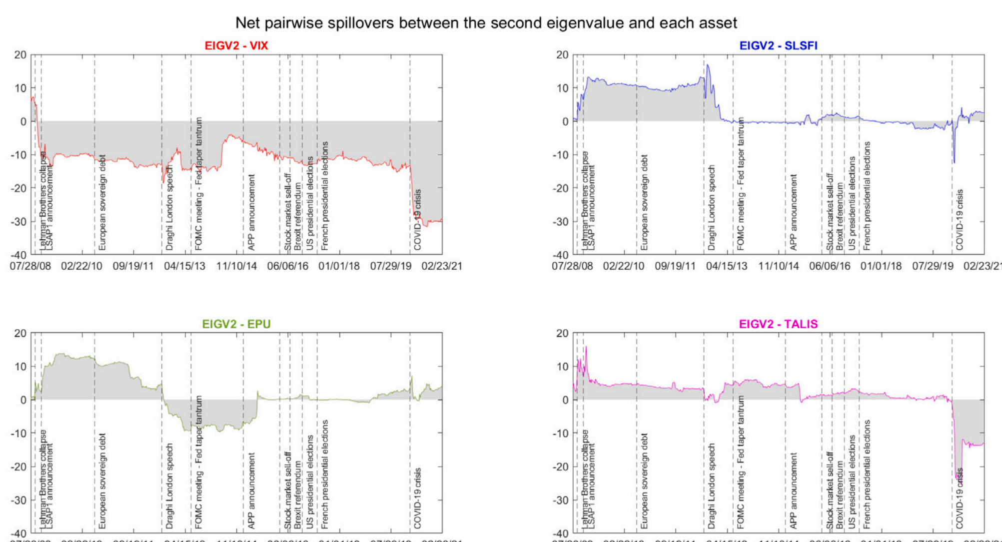

Fig. B.1. Net pairwise spillovers between the square root of the second eigenvalue (EIGV2) and CBOE Volatility Index (VIX), St. Louis Fed Financial Stress Index (SLFSI), Economic Policy Uncertainty Index (EPU), and TrAffic LIght System for Systemic Stress (TALIS) variables.

spillover analysis neither detected nor explained the greater proportion of variation explained by the first PC (commonality) during larger periods of financial stress. The closer look at the eigenvectors shown in Section 3 contributes substantially to explaining the component of comovement in intraday stock returns that volatility spillover analysis might neglect.

Finally, Fig. 14 reports a comparison between the net volatility spillover of the four indices and that of EIGV1. Net volatility spillovers indicated the difference between the gross volatility shocks transmitted to and those received from all other variables. Shocks to the volatility of the first PC, EIGV1, have a positive net impact (give more than receive) until 2013 when it turned negative (give less than receive). We observed that VIX was a strong volatility transmitter (large and positive values) throughout the period. SLFSI received more than it gave to the rest of the indices. The EPU index appeared only as a volatility spillover transmitter between 2011 and 2014. Finally, TALIS received more than it gave to the rest of the indices for almost the entire period considered, except for the last part of the sample, that is, the COVID-19 period, when the net volatility spillovers turned positive, reaching 20% at the very beginning of the pandemic.

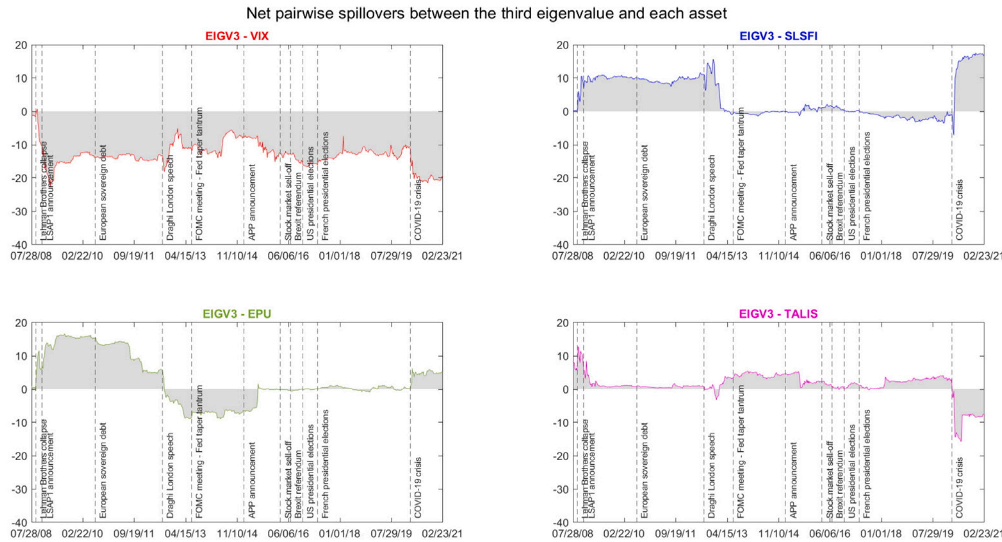

Fig. B.2. Net pairwise spillovers between the square root of the third eigenvalue (EIGV3) and CBOE Volatility Index (VIX), St. Louis Fed Financial Stress Index (SLFSI), Economic Policy Uncertainty Index (EPU), and TrAffic LIght System for Systemic Stress (TALIS) variables.

Table B.1
Volatility spillovers across the second eigenvalue (EIGV2) and the macro-financial variables for the full sample period.

	EIGV2	VIX	SLFSI	EPU	TALIS	*From Others*
EIGV2	61.666	27.129	3.082	1.814	6.309	38.334
VIX	8.864	70.657	0.943	1.535	18.002	29.343
SLFSI	11.187	10.053	75.318	0.984	2.458	24.682
EPU	5.491	4.969	0.100	87.562	1.879	12.438
TALIS	2.159	24.201	0.369	0.001	73.270	26.730
To others	27.701	66.352	4.494	4.334	28.647	*Total Spillover Index*
NET	−10.633	37.009	−20.189	−8.105	1.917	**26.306**

6. Concluding remarks

In this paper, we combined HF econometrics and large-dimensional factor analysis using PCA to approximate the informative content of an HF dataset. The analyses we develop contribute to the scarce literature that focuses on HF factors to capture the level of stress in the financial market.

The empirical analysis carried out in this study using one-minute returns of stocks included in the Russel 3000 index from 2003 until 2021 shows that largely realized eigenvalues overlap with important events associated with both US and EU monetary policy announcements or other macro events. There appears to be a clear relationship between eigenvalues and systemic increases in financial stress. We also found that realized eigenvectors can trace the role of firms/sectors as potential sources of financial stress in different periods of time.

The study of weekly realized eigenvectors is of great importance in understanding and tracking the complex behavior of the financial sector during different periods. Simple visual analysis has shown that the distribution of the eigenvector might offer a good deal of information on which to follow-up and anticipate financial turbulence. These results will allow policymakers to continuously monitor the market structure in almost real-time and allow the design of a better strategy to identify systemic states.

Beyond understanding the structure of the financial market, policymakers are also interested in identifying the mechanisms through which the rich set of information contained in the stock prices of financial companies propagates to other markets, helping to predict future financial instability. Using the Diebold–Yilmaz methodology to identify spillover effects between volatility in the stock prices of the US financial sector and the commonly used macro-finance uncertainty indicators, we have shown that the information extracted from the HF comovement at stock prices is carried over to policy and financial uncertainty indicators.

In summary, using one-minute stock prices provides an effective tool for supervisors and policymakers in rapidly evolving uncertain times (Global Financial crisis, COVID-19, Silicon Valley Bank collapse) that permits rapid estimates and updates of financial stress and, consequently, of systemic risk mainly under unstable conditions. One of the main is to help policymakers identify and monitor stress levels in the financial system that may be of serious concern. The combination of HF with PCA allows us to obtain instantaneous eigenvalues, eigenvectors, and realized principal components over short windows of observation and relatively large dimensions, without the need to impose strong parametric assumptions on the distribution of the data. All this information has something important to say about the instantaneous correlations among assets and the collective response of the entire market to shocks such as certain news breaks (e.g., central bank interest rate hikes). Therefore, the tools used in this paper can keep pace with financial conditions that seem to change overnight. Such tools allow policymakers to track how the rich set of information contained in the stock prices of financial institutions propagates to other markets, helping to detect financial instability and crisis.

The statistical tools are enhanced by static and dynamic loading plots as an effective and intuitive procedure to visually understand in two-dimensional planes how the internal structure of the financial system changes over time. Loading plots are linear projections of the data onto two-dimensional planes that attempt to preserve the inter-class structure present in the original multidimensional space. In this sense, policymakers and investors will have access to real-time, interactive visualization toolboxes that will allow the user to compute different individual or global, static or dynamic views of the entire financial system.

This work will also be useful for investors, not only for tracking the stability of the financial system, but also because instantaneous eigenvalues and eigenvectors can be used to build portfolios with intraday updates of the weights, which as shown by Chen et al. (2020), can be an advantage during turbulent periods.

This research represents a first step towards bringing HF PCA tools to the vast literature of systemic risk analysis and bringing real-time visualization toolboxes as a quick and intuitive way of tracking the evolving structure of the financial market in real-time. One limitation of this paper, which we hope to pursue in future extensions, is that it is

Table B.2
Volatility spillovers across the third eigenvalue (EIGV3) and the macro-financial variables for the full sample period.

	EIGV3	VIX	SLFSI	EPU	TALIS	*From Others*
EIGV3	62.333	26.325	5.036	1.932	4.374	37.667
VIX	10.213	69.508	0.846	1.383	18.050	30.492
SLFSI	14.420	9.267	72.996	0.749	2.567	27.004
EPU	5.978	4.904	0.173	87.068	1.878	12.932
TALIS	2.460	24.167	0.381	0.002	72.990	27.010
To others	33.071	64.663	6.436	4.066	26.869	*Total Spillover Index*
NET	−4.596	34.171	−20.568	−8.866	−0.141	**27.021**

based only on in-sample information. Out-of-sample forecasting would provide an invaluable tool for using information extracted from high-frequency comovement in financial asset prices to anticipate or smooth the occurrence of financial and banking turbulence.

Thus, as further research, our work is open to implementing strategies to make predictions of realized eigenvalues and eigenvectors from HF data. One option to examine is to use parametric and semiparametric models to predict weekly spot-realized covariance matrices. This would allow the construction of out-of-sample dynamic biplots to provide a visual representation of the expected structure of the financial system to identify in advance strong and spreading financial stress that could become systemic. Ongoing research shows that measures based on the distance between pairs of predicted eigenvectors at t+h and the observed t weighted by the variance of these predictions appear to be able to forecast financial turbulence in both the financial sector and individual institutions.

CRediT authorship contribution statement

Massimiliano Caporin: Data curation, Conceptualization, Methodology, Software, Writing – review & editing. **Laura Garcia-Jorcano:** Data curation, Methodology, Software, Writing – review & editing. **Juan-Angel Jimenez-Martin:** Methodology, Software, Writing – original draft, Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Company's names

See Tables A.1 and A.2.

Appendix B. EIGV2 and EIGV3 volatility spillovers

See Figs. B.1 and B.2 and Tables B.1 and B.2.

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