Contagion Among the GSIB's: Does Regulatory Intervention Matter?

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Abstract

This paper compares two methods for assessing the contagion of risk among ten Globally Significant International Banks, known as GSIBs, listed on the New York Stock Exchange with daily data from 2007 to 2020. In particular we are interested in identifying the banks which are the largest net sources or transmitters of risk to the banking system as a whole. We also examine the role of regulatory interventions, in the form of bank fines and BIS Bin Classification for capital adequacy. Under alternative measures, the frequency and total amount of bank fines, as well as the BIS Capital Adequacy, have statistically significant relationships with only a few banks among the GSIB's. We argue that our measures of contagion can serve as useful tools for regulators for identifying the sources of contagion within banking networks and make such regulatory interventions more effective instruments for financial stability.

Key words: contagion, forecast-error variance decomposition, conditional value at risk, Elastic Net estimation, Cross-Validation

1 Introduction

This paper focuses on the measurement of risk and the contagion or spread of such risk among ten Globally Significant International Banks (GSIBs) listed on the New York Stock Exchange. Given that there are different methods for measuring risk and the contagion effects of such risk, do any of these ten banks stand out, across various measures, as significant sources of contagion of such risk across the banking sector? If so, do regulatory measures, in the form of the frequency and amounts of bank fines or BIS Bin classifications for capital-adequacy ratios, have any effect on banking sector contagion measures?

Risk, of course, is a latent variable, not directly observable but important, for which we create proxy measures. One commonly used measure is variance or volatility. For example, a return which has greater volatility, *mutatis mutandis*,

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has more risk than another variable with lower volatility. Usually variance is a measure of the second moment of a series, much like the mean. To obtain measures which evolve over time, one measure is the conditional volatility obtained from Generalized Autoregressive Conditional Volatility (GARCH) models, pioneered by Engle (1982). Another approach for time-varying measures of risk is implied volatility, obtained from pricing of assets on options markets [see Beckers (1981)]. A third measure is realized volatility, obtained from standard deviations measured from higher-frequency data, for use as a time-varying measure for daily or lower frequency data [see Andersen et al. (2003)]. A popular approximation to the realized volatility measurement is range volatility, introduced by Garman and Klass (1980). This measure makes use of opening, closing, and high and low measures of an an asset price, and thus avoids the need to delve into higher frequency data, such as minute-by-minute data, for obtaining daily time-varying measures of volatility.

Diebold and Yilmaz (2013) have used these last measures of risk in a Vector Autoregressive (VAR) model to assess the connectedness of risk among various markets or financial units. From VAR estimation, with out-of-sample forecasting, they obtained the asymmetric Forecast Error Variance Decomposition matrix. If the realized volatility of a unit has a larger own FEVD than another unit, it is, by definition, harder to forecast and thus more risky. The operating assumption is that risk measures come from forward-looking estimates of volatility. Similarly, if one unit has a high covariance with another unit, than the other unit has with it, it is a net transmitter of risk to the other unit. With this method, one can identify which units are net transmitters of risk to other units, as well as to the system as a whole.

Another market measure of risk of particular assets comes from the Credit Default Swap (CDS) markets. We examine the interconnections of risk premia for these instruments. This market is relevant, of course, for bond holders rather than share holders in the GSIB's. Unlike the shareholders, they are not residual claimants. However, the movements of such premia should move in tandem with share-price range volatility.[1]

Mihai and Neagu (2011) examined the usefulness of these measures for the risk of soverign government bonds for Romania. Relative to interest-rate spreads, they found that these data provided little additional information for financial stability analysis. However this does not mean that information from CDS premia cannot service as robustness checks on alternative measures of market risk.

However, as noted more that fifty years ago by Rothschild and Stiglitz (1970), the relationship between volatility and various forms of risk, is more complex. Risk is not only a measure of the width of a probability distribution. We are not at risk of outcomes on the right tail, but we are at risk for down-side events. Put another way, do we treat upside outcomes equally as we do downside risk? Rather than using overall volatility measures, an alternative is to use

[1]Since data are not available for the full set of the listed GSIB's for CDS premia, we compare the results for range volatility and CDS premia for ten banks, for which we have realized volatilities and CDS premia.

quantile regression to obtain a probability, for given factors, of landing below critical values on the left tail of the distribution of returns [see, for example, Chiang and Li (2012)]. Adrian and Brunnermeier (2016) extended this approach with a definition of risk as the probability measure of how far an outcome deviates from the median outcome. From this, they obtained, with quantile regression a measure of how one return affects the probability of the market as a whole deviating from the median return. They call this estimate $\Delta Covar$, where Covar is Conditional variance at risk. As a further robusteness check on the Diebold-Yilmuz range volatility measures, we also examine the inter-bank transmission of risk with this measure.

The next section summarizes the data and the controls we use for the ten GSIB's banks over the period 2007-2021. In succeeding sections, we apply our two methods, FEVD (for both range volatility and CDS premia) and $\Delta Covar$. Then we compare the results for the overall sample and with time-varying parameter estimation. The final section is the conclusion.

2 The GSIB: Risk Measures and Control Variables

Table 1 lists the ten GSIB's we use for our study, with the median, max and min values for the full period. We normalize each series by dividing the daily index values by the first observation of each index, and then take natural logarithms. We see over this period that for most of the banks, the mean and median returns have been negative, due to the Global Financial Crisis in 2008. There are some exceptions such as J.P Morgan Chase and Wells Fargo. The Royal Bank of Scotland had the most negative value for the mean change relative to the initial value.

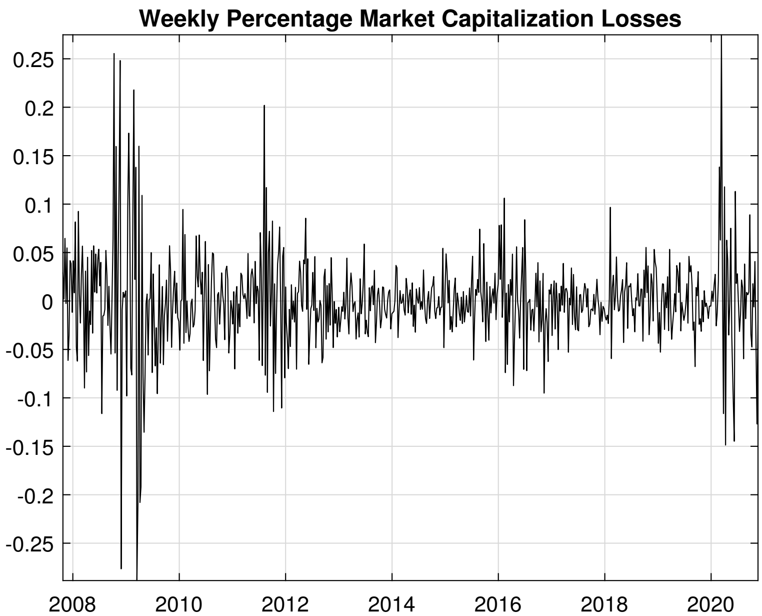
Table 1: GSIB Returns and Credit Deault Swap (CDS) Premia 2007-2020

		GSIB Returns					CDS Premia		
Code	Name	Type3*	Mean	Median	Max	Min	Mean	Median	Max
BAC	Bank of America		-0.304	-0.280	0.438	**-2.378**	0.941	0.804	**2.571**
BK	Bank of New York Mellon		-0.290	-0.275	0.138	-0.923	1.205	1.117	2.690
BCA	Barclays		-0.605	-0.551	0.022	**-2.558**	1.087	1.047	**2.199**
BBVA	Banco Bilbao Vizcaya Argentaria		-0.651	-0.639	0.034	-1.715	0.983	0.826	2.833
C	Citigroup		-0.604	-0.455	0.000	**-3.664**	0.940	0.918	**2.037**
GS	Goldman Sachs		-0.248	-0.220	0.106	**-1.367**	0.657	0.537	**2.251**
JPM	JP Morgan Chase		0.328	0.323	1.054	-0.948	0.651	0.616	1.830
MS	Morgan Stanley		-0.269	-0.212	0.427	**-1.961**	0.736	0.568	**3.173**
SAN	Santander		-0.426	-0.409	0.138	**-1.458**	1.116	1.064	2.638
WFC	Wells Fargo		0.481	0.593	1.053	**-1.191**	0.859	0.769	**2.344**

*Unless noted, listed on the NYSE.

The weighted weekly returns for all ten appear in Figure 1. We see the greatest volatility at the time of the Global Financial Crisis, but also in 2012, at the time of the downgrading of the US debt, and at the start of the COVID19 period.

Figure 1: Weighted Weekly Changes in Market Capitalization



For understanding the interaction among these banking units we make use of the control variables listed in Table 2. These variables were used by Adrian and Brunnermeier (2016) in their approach to contagion. The mean and median values of the change in the Tbill are practically zero. We also see drastic changes in the spreads as well as in corporate and real estate excess returns over the sample period.

Table 2: Control Variables

	Mean*	Median	Std Dev.	Max	Min
Fed Funds Rate	0.724	0.170	0.955	4.860	0.040
$\Delta Tbill$	-0.001	0.000	0.084	3.000	-0.895
Credit Spread	2.798	2.700	0.771	6.160	1.560
Liquidity Spread	0.114	0.080	0.148	1.320	-0.870
TED Spread	0.429	0.270	0.462	4.580	-0.260
Yield Spread	1.857	1.930	0.988	3.830	-0.520
DJ Corp Ex Ret	0.000	0.000	0.004	0.045	-0.040
DJ Real Estate Ex Ret	0.000	0.000	0.014	0.144	-0.138
VIX	20.157	17.135	9.916	82.690	9.140

*Percentage values.

Table 3 summarizes the regulatory experience of the GSIB's during the sample period in terms of the frequency and amount of bank fines as well as the respective maximum BIS Bin Classification (ranging form 1 to 4) for capital adequacy ratios.[2]

We put in bold the numbers for the top five banks. BAC leads the pack for the largest individual fine of $16 billion in August 2014. It also leads in terms of total fine amounts and frequency of fines during the sample period. JPM is not far behind, and is also in the highest Bin for the BIS ratios. However, WFC, which is second in frequency of fines and among the top five GSIB's in total fines, is in the lowest BIS bin.

We also note that some of the maximum value fines took place within three years after the GFC. After that period, many of the maximum fines were associated with the LIBOR manipulation scandal.[3]

Table 3: GSIB Regulatory Experience

	Fine History				BIS
Bank Name:	Maximum Value	Date of Fine	Total Fine Amount	Frequency	Bin
BAC	**$16,650,000,000**	21-Aug-14	**$60,130,305,938**	**143**	3
BK	$714,000,000	19-Mar-15	$1,190,079,484	17	2
BCA	$2,000,000,000	29-Mar-18	$4,101,908,033	24	3
BBVA	$27,000,000	21-Dec-16	$38,587,250	6	1
C	**$7,000,000,000**	14-Jul-14	**$14,335,859,039**	24	**4**
GS	$5,060,000,000	**11-Apr-16**	$9,437,424,794	21	2
JPM	**$13,000,000,000**	19-Nov-13	**$26,398,442,855**	**99**	**4**
MS	$2,600,000,000	11-Feb-16	$5,112,697,271	**90**	2
SAN	$550,000,000	19-May-20	$637,058,281	19	1
WFC	$5,342,200,000	9-Feb-12	**$19,280,766,695**	**117**	2

The question of this paper: given the controls, do any of the banks among the GSIB's stand out as the major sources of systemic risk for the weighted returns of the banking system as a while? Secondly, do regulatory interventions, in the form of the size and frequency of fines, and BIS bin classifications, have any relation to banks which are net sources of contagion among the GSIB's?

3 Method of Analysis

In this section we briefly summarize the FEVD and the $\Delta Covar$ methods for identifying which banks among the GSIB's are the major sources of risk, conditional on the controls

3.1 FEVD Method

The realized daily range volatility measure, due to Garman and Klass (1980)denoted by σ_t^R, comes from an approximation based on spreads between the daily

[2] The BIS Basel III classifications began after the start of the sample, in 2013.

[3] See https://en.wikipedia.org/wiki/Libor_scandal

opening (o) and closing (c), as well as maximum (h) and minimum (l) of the natural logarithmic values of the share prices observed each day.

$$\sigma_t^R = .511(h-l)^2 - \hat{.019}[(c-o)(h-l-2o) - 2(h-o)(l-o)] - .383(c-o)^2 \quad (1)$$

For the FEVD method, we estimate a VAR-X model for the ten banks with daily data with five lags. We also have as "controls" the nine controls, for the following VARX model:

$$[(I - \Theta(L)]Y_t = \Gamma X_{t-1} + U_t \quad (2)$$

$$U_t \sim N(0, \Sigma) \quad (3)$$

where the parameter matrix Θ is the set of coefficients for the lagged state variables, and Γ the matrix of coefficients of the lagged controls on the current dependent variable. The matrix U is the n by 10 set of shocks, which is distributed with mean zero and variance-co variance matrix Σ. We rule out auto correlation but not contemporaneous correlation in the shocks.

To reduce the number of coefficients we use the Elastic Net method based on Zou and Hastie (2005):

$$\beta_{Enet} = \overset{Min}{\beta} \left\{ \sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{k} \left[(\alpha|\beta_i|) + (1-\alpha)\beta_i^2 \right] \right\} \quad (4)$$

This method involves minimizing the sum of squared residuals with a penalty term on the sum of the absolute values or squared values of the coefficients of the model, β,which capture the elements of the Θ and $\mathit{\Gamma}$. For setting $\alpha = 1$,the method reduces to LASSO (Least Absolute Shrinkage Selection Operator), while $\alpha = 0$ reduces to Ridge Regression.

To find the optimal value o λ,we use Cross Validation (CV). With CV, select a grid of values for λ, between $\lambda = 0$,which reduces to Last Squares and λ^*, the minimum λ which sets all of the coefficients $\beta_i = 0$. We then select a set of out-of-sample Mean Squared Error measures, based on holding out 20% of the sample for each specified λ over the grid. The optimal λ minimizes the average out-of-sample mean squared error.

For analysis of the CDS premia, the optimal lag length is much shorter, with a lag length of two, for ten state variables and the same controls. We apply the Elastic Net estimation method to these data.

Once the model is estimated by the Elastic Net, we can extract information about the contagion of risk with the Forecast Error Variance Decomposition. The estimated parameters do not have any information by themselves. We are not interested in tests about specific values of any of the parameters. We use the estimated variance-covariance matrix of the estimated shocks to forecast each of the variables for 15 days forward. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables after a given horizon. It is an asymmetric matrix, so that one variable may have greater outward connectedness to the others and thus may be a major source of systemic risk.

It should be noted that by reducing the number of coefficients, the use of the Elastic Net estimation biases the results toward less interconnectedess rather than more. Thus the results which emerge from the FEVD analysis based on Elastic Net estimation represent significant measures of interconnectedness, since these results come from parameters which have survived a thorough winnowing process.

To better capture the dynamics of the changing patterns of connectedness, we estimate equation (2) for the full sample and then as a rolling window regression. In this way, the linear specification not only is able to approximate more accurately the structural changes which took place in the financial system during the estimation period, but also, as noted by Granger (2008), capture the effects of any neglected nonlinear relations. See Diebold and Yilmaz (2012) for further elaboration.

3.2 $\Delta Covar$ Method

One way to evaluate risk in financial regression is through quantile regression. We can use this tool to predict Value at Risk (VaR) from a given probability distribution.[4] VaR in the above distribution is the value of the returns at the lowest 5% probability in the left tail of the distribution. Simply multiply the value of the market capitalization and this value, and we have an estimate of the VaR for the Market at the 5% probability. We can forecast the VaR from a set of covariates or x-variables with Quantile Regression.

In Linear Least squares (OLS), with an intercept, we fit the regression line through the mean of the dependent variable. In quantile regression, for a given probability τ, we fit the regression line through the value of the dependent variable at the quantile τ. We find the parameters by minimizing the sum of **absolute deviations**, rather than squared deviation. For predicting the median, we set $\tau = .5$.

The $\Delta Covar$ method is an application of quantile regression due to Adrian and Brunnermeier (2016). The method involves the following steps:

1. Take the negative of the weighted returns of the banking, except for bank (i), so that the 95% quantile is the lower 5% quantile for $\tau = .05$,

2. Do a quantile regression for $\tau = .95$ of the weighted market returns on bank(i) returns and the controls. Obtain $VaR^i_{\tau=.95}$,

3. Do a quantile regression for $\tau = .50$ of the market returns on bank(i) returns and the controls. Obtain VaR,

4. Calculate $\triangle CoVar(i)$= $VaR^i_{\tau=.95} - VAaR$,

[4]Note that VAR denotes Vector Autoregressive Model while VaR is used for Value at Risk.

5. Repeat for all of the banks.

We then have a measure of the relative importance of each bank to the overall weighted market risk of the system as a whole.

The common sense of this method: it tells us how much returns of Bank (i) put the system at risk of diverging by 45% below the median. It will tell us which banks play stronger roles in putting the system at such risk, more than other banks.

For purposes of this analysis we will examine how each of the ten banks affect the risk of the market return.

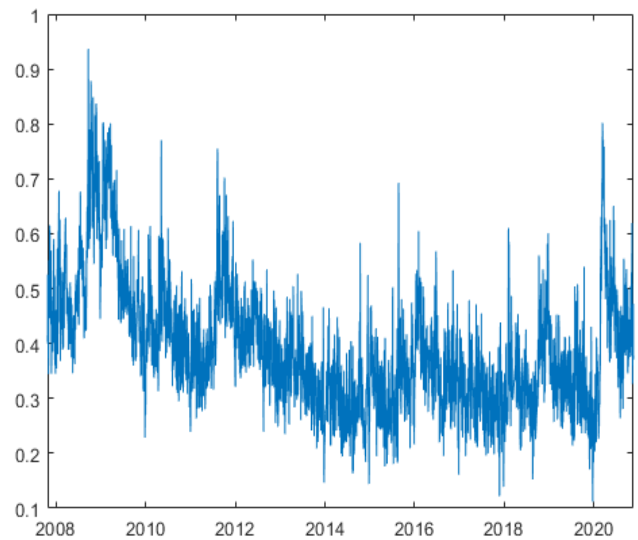
4 FEVD Results on Contagion: Range Volatility

4.1 Normalized range volatility

The median range volatility for all of the banks, calculated from formula (2), appears in Figure 2. The volatilites are normalized logrithmic values of the Garmin-Klass calculations. Diebold and Yilmaz (2012) suggested the logarithmic transformation of these values. The normalization between [0,1] allows faster convergence during the estimation process.

The calculated volatility is largest around the time of the Global Financial Crisis. However, while volatility diminished after 2010, it has by no means disappeared. There were jumps in volatility values at the time of the downgrading of US Debt in 2012, at the time of Brexit in 2016, the incipient trade tensions with China in 2019 and of course in 2020 at the time of the COVID19 pandemic.

Figure 2: Median Range Volatility of the GSIB's



4.2 Full-sample estimation results

The Net Connectedness measures of the GSIB's, based on full-sample estimation with Elastic Net and Cross Validation, appears in Figure 3. This figure shows that BCA and BAC, followed by CS and SAN, have outward connectedness. The overall spillover index for the full sample, based on the Forecast Error Variance-Decomposition matrix, is .8651. This index is defined as the sum of the elements of the matrix, net of the diagonal elements, relative to the sum of all of the elements. This value is consistent with a relatively high degree of connectivity among the ten GSIB's.

The bi-variate pattern of connectivity among the GSIB's is pictured in the GSIB Network in Figure 4. Figure 3shows the relative strenth of outward and inward connectedness for each bank with the system as a whole. Figure 4 shows the bivariate system of connectivity. The banks in the center of the network chart, BBVA and BCA, have the largest number of bivariate connections within the system as a whole. BCA stands out in both figures for strength of outward connectedness as well as number of bivariate connections.

4.3 Results with rolling-window estimation

Of course, as noted above, some banks may have been more important at specific times and less important at other times. For this reason we make use of rolling-window estimation. Figure 5 pictures the mean values over the sample with a moving window of size 300. The results are broadly consistent with full-sample

Figure 3: Range Volatility Net Connectedness, Full-Sample Estimation

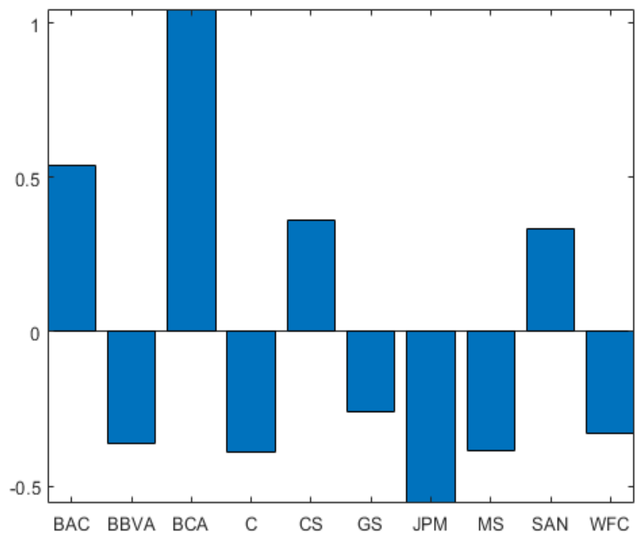


Figure 4: Range Volatility Network and Clustering: Full-Sample Estimation

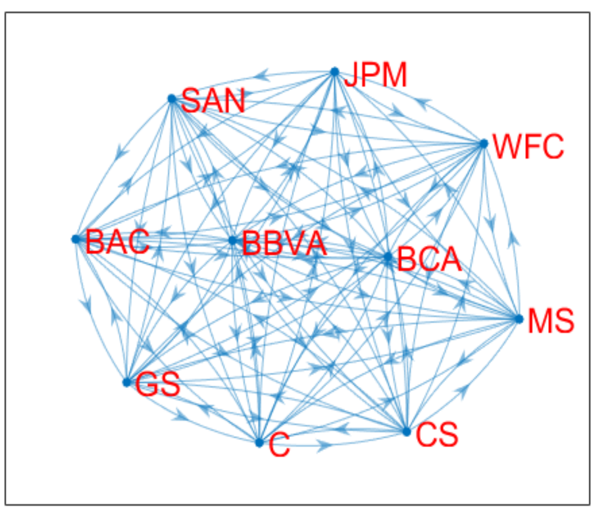
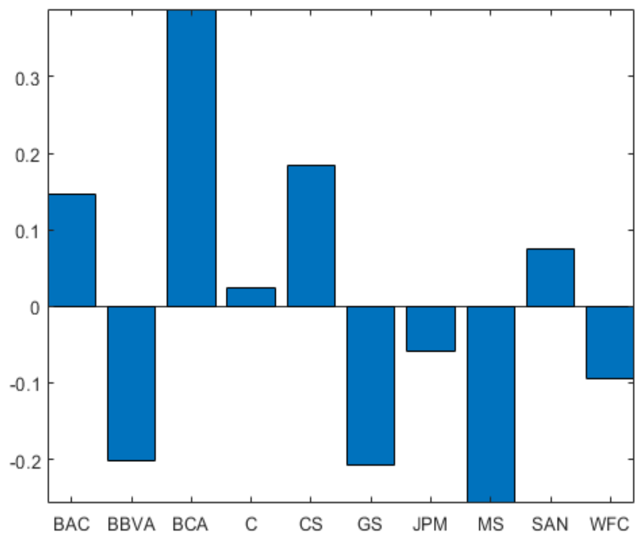


Figure 5: Net Connectedness: Mean of Moving Window



estimation with BCA and BAC standing out as the banks with the largest outward-connectedness on average.

To explore further the dynamics of banking connectedness, we show in Table **??** the maximum values as well as the dates of each bank's maximum estimated net connectedness measures.

We see that while BCA has the largest average net connectedness measure, BBVA has the largest maximal net connecteness measure, which took place in 2014, after a writedown on a purchase of a US digital bank, followed by SAN, which happened in July 2019, when it cancelled dividend payments, and then GS, which took place in 2010 in the wake of the GFC.[5] While it is not clear that specific events triggered the maximum contagion effects for specific banks, these events provide a narrative for understanding why these contagion effects reached their peak values.

4.4 Regulatory interventions and contagion

To evaluate the relation between regulatory interventions and banking sector contagion, we make use of a Feed Forward Neural Network, linking each bank's

[5] see https://www.marketwatch.com/story/banco-santander-cancels-2019-final-dividend-2020-04-03-14852439 for SAN,and https://archive.nytimes.com/dealbook.nytimes.com/2014/02/20/bbva-buys-banking-start-up-simple-for-117-million/ for informaiton on BBVA.

Table 4: GSIB Connectedness: Maximum Values

Bank	Max Val	Date
BAC	4.966	6-Jun-18
BBVA	8.046	22-Sep-14
BCA	4.124	28-May-13
C	6.494	26-Dec-14
CS	5.074	3-Jan-11
GS	6.564	1-Sep-10
JPM	5.539	22-Jun-18
MS	5.690	16-Nov-18
SAN	7.277	18-Jul-19
WFC	5.423	24-Jun-10

connectedness with its lagged fine history and BIS classification.

The nonlinear feed forward network forms neurons from linear combinations of the input data by transforming these combination with a logsigmoid function, as shown in equations (5) through (6). In a shallow network with one hidden layer, the neurons are then combined in a linear fashion to forecast the dependent or target variable y.

$$n_{k,t} = \omega_{k,0} + \sum_{i=1}^{i*} \omega_{k,i} x_{i,t} \tag{5}$$

$$N_{k,t} = \frac{1}{1 + e^{-n_{k,t}}} \tag{6}$$

$$= \Sigma(n_{k,t}) \tag{7}$$

$$y_t = \gamma_0 + \sum_{k=1}^{k^*} \gamma_k N_{k,t} \tag{8}$$

The symbol Σ represents the sigmoid function, also known as the logit or logistic function. The appeal of the logsigmoid transform function comes from its "threshold behavior" which characterizes many types of economic responses to changes in fundamental variables. For example, if interest rates are already very low or very high, small changes in this rate will have very little effect on the decision to purchase an automobile or other consumer durable, for example. However within critical ranges between these two extremes, small changes may signal significant upward or downward movements and therefore create a pronounced impact on automobile demand.

Furthermore, the shape of the logsigmoid function reflects a kind of learning behavior. Often used to characterize "learning by doing", the function becomes increasingly steep until some inflection point. Thereafter the function becomes increasingly flat up and its slope moves exponentially to zero. Following the same example, as interest rates begin to increase from low levels, consumers will judge the probability of a sharp uptick or downtick in the interest rate based on the currently advertised financing packages. The more experience they have, up to some level, the more apt they are to interpret this signal as the time to take advantage of the current interest rate, or the time to postpone a purchase. The results are markedly different than those experienced at other points on the temporal history of interest rates. Thus, the nonlinear logsigmoid function captures a threshold response characterizing "bounded rationality" or a "learning process" in the formation of expectations.

Kuan and White (1994) describe this threshold feature as the "fundamental" characteristic of nonlinear response in the neural network paradigm. They describe it as the "tendency of certain types of neurons to be quiescent of modest levels of input activity, and to become active only after the input activity passes a certain threshold, while beyond this, increases in input activity have little further effect.

A multilayered feedforward network would combine the neurons in equation (10) into a new set of linear combinations, which are, in turn, transformed by a logsigmoid function, as show in the following system:

$$n_{k,t} = \omega_{k,0} + \sum_{i=1}^{i*} \omega_{k,i} x_{i,t} \tag{9}$$

$$N_{k,t} = \frac{1}{1 + e^{-n_{k,t}}} \tag{10}$$

$$p_{l,t} = \rho_{l,0} + \sum_{k=1}^{k^*} \rho_{l,k} N_{k,t} \tag{11}$$

$$P_{l,t} = \frac{1}{1 + e^{-p_{l,t}}} \tag{12}$$

$$y_t = \gamma_0 + \sum_{l=1}^{l^*} \gamma_l P_{l,t} \tag{13}$$

In our estimation we employ a deep-learning network with ten neurons in three hidden layers, with one lag for the three regulatory instruments (the fine amounts, fine frequency, and the BIS bin classifications). We estimate the model for the sample beginning in March 2013, when the BIS bin classifications were implemented for all of the GSIB's.

Table **??** contains the overall coefficient of determination of the ten regressions as well as its significance level. We see that for four banks, BCA, CS, SAN, and WFC, the regressions are significant. Table **??** also gives the partial derivatives, evaluated at the mean values, for the BIS Bin classifications, the

Fine Amounts and Fine Frequency. For BCA, both the fine amounts and the BIS Bin classificaitons have expected negative effects on contagion. For CS, SAN, and WFC, where the regressions are significant, the amount of the fines appear to have the strongest effects for reducing contagion.

Table 5: Nonlinear Regression of Connectedness on Regulatory Interventions

			Partial Derivatives:		
Bank Name	RSQ	P-Val	Fine Frequency	Fine Amount	BIS Bin
BAC	0.007	0.999	0.095	-0.294	-0.012
BBVA	0.006	1.000	0.157	-0.090	-0.011
BCA	0.034	0.001	0.136	-0.206	-0.040
C	0.003	1.000	-0.014	-0.229	-0.010
CS	0.041	0.000	-0.046	-0.753	-0.066
GS	0.001	1.000	-0.039	-0.420	0.093
JPM	0.001	1.000	-0.016	-0.282	0.062
MS	0.002	1.000	0.010	-0.054	0.008
SAN	0.038	0.000	-0.019	-0.159	0.048
WFC	0.242	0.000	0.065	-0.160	0.087

5 FEVD Results on Contagion: CDS Premia

5.1 Normalized CDS premia

Figure 6 pictures the median values of the rate of change of the CDS premia for the ten banks. We see that the periods of greatest volatility were at the time of the Global Financial Crisis after 2008, as well as after 2020, the time of the COVID19 pandemic. However there were also spikes at time of Brexit in 2016 and at the time of the downgrading of US Debt in 2012.

5.2 Full sample estimation results

Figure 7 pictures the net connectedness measures based on full-sample estimation with Elastic Net. This figure shows some consistencies with the connectedness measures based on range volatility. In particular, both BAC and BCA have positive effects on the CDS premia of the banking sector. But in the CDS market, JPM and MS have positive outward connectedness, as opposed to negative connectedness with respect to range volatility.

The directional graph for the CDS premia shows that both BBVA and BCA are at the center of bivariate clustering. This chart is practically identical to the bivariate clustering of the range volatility measures.

Figure 6: Median Rate of Change of the CDS Premia

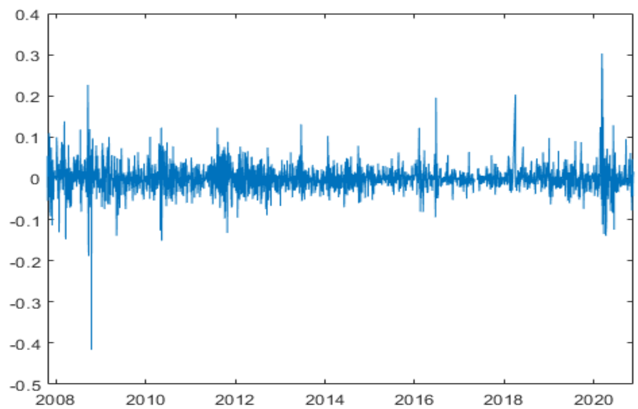


Figure 7: CDS Net Connectedness, Full Sample Estimation

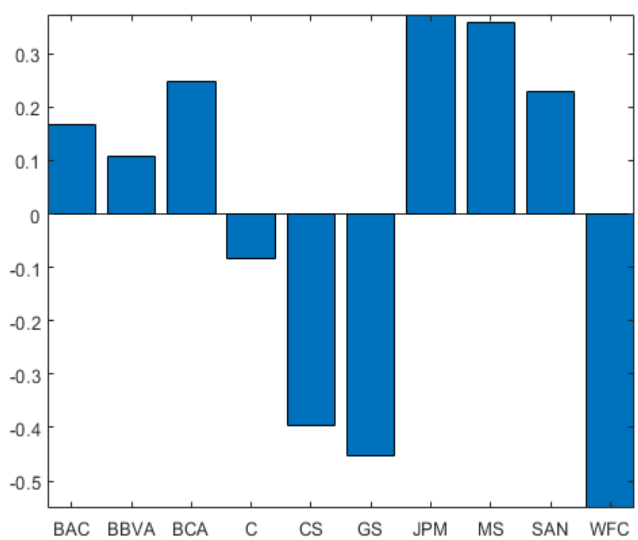
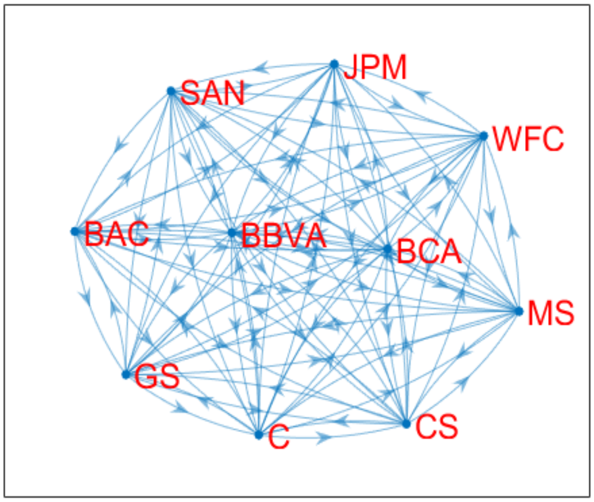


Figure 8: CDS Premia Network and Clustering: Full-Sample Estimation



5.3 Results with moving-window estimation

Figure 9 pictures the mean of the net connectedness of the CDS market. As in the case of the range volatility, we see that BCA stands out as the major source of outward transmission of risk in this market, based on the mean values of the rolling-window estimates.

As above, Table 6 pictures the maximum values of the outward connectedness as well as timing of these values but for the CDS premia. This table shows that the largest of the maximum contagion effects, for BAC and JPM, took place in the wake of the GFC. The third largest of the max values belongs to BCA. In the CDS market, this contagion effect took place in 2016 in the lead up to Brexit.

5.4 Regulatory intervention and contagion

Table 7 contains the overall coefficient of determination of the ten regressions as well as its significance level. We see that for four banks, BAC, BBVA, BCA, and WFC, the regressions are significant and the regulatory interventions have the expected negative signs, implying that these interventions reduce the outward contagion effects of this banks under intervention. However for MS, the coefficients are jointly significant but the partial derivatives, while small, are positive. We found similar results for range volatility-based measures for BCA and WFC.

Figure 9: CDS Net Connectedness: Mean of Moving Window

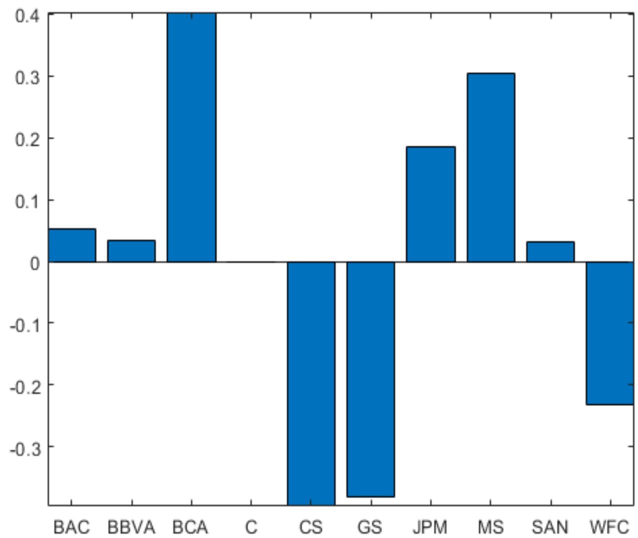


Table 6: CDS Connectedness: Maximum Values

Name	Max Val	Date
BAC	5.308	12-Oct-11
BBVA	3.258	23-Sep-19
BCA	4.472	18-Feb-16
C	3.465	11-Jun-09
CS	2.461	8-Nov-19
GS	0.620	12-Mar-20
JPM	4.895	23-Sep-09
MS	2.204	6-Oct-11
SAN	3.903	28-Oct-10
WFC	2.093	3-Oct-11

Table 7: Nonlinear Regression of Connectedness on Regulatory Interventions

			Partial Derivatives		
Bank Name	RSQ	P-Val	Fine Frequency	Fine Amount	BIS Bin
BAC	0.057	0.000	-0.107	-0.202	-0.115
BBVA	0.121	0.000	-0.014	-0.027	-0.013
BCA	0.065	0.000	-0.022	-0.042	-0.022
C	0.004	1.000	-0.039	-0.079	-0.042
CS	0.000	1.000	0.000	0.000	0.000
GS	0.000	1.000	-0.001	-0.003	0.002
JPM	0.000	1.000	-0.001	-0.003	0.002
MS	0.055	0.000	0.004	0.007	0.003
SAN	0.023	0.114	-0.012	-0.027	-0.005
WFC	0.155	0.000	-0.007	-0.747	-0.565

6 $\Delta Covar$ Results on Contagion

6.1 $\Delta Covar$ statistics for $\tau = .95$

Figure 10 pictures the maximum values of the set of the ten GSIB's at each period of the sample, based on the rolling-regression estimation. Similar to the results based on range volatility, we see that the maximum contagion effects by particular banks take place at the time of the Global Financial Crisis after 2008, at the time of the downgrading of US debt in 2012, and after the start of the COVID19 pandemic in 2020.

Table 8 gives the relevant maximum values as well as the dates of these values. We see that the maximum values for all of the banks took place shortly after the start of the Global Financial Crisis in 2008. The top five generators of systemic risk by this method are SAN and CS, followed by BBVA. SAN and BBVA are also among the leaders for Net Connectedness based on the range volatility approach of Diebold and Yilmaz (2014) but under the Range Volatility approach, the max values come at later dates.

Despite some overlap of two banks appearing among the top five net transmitters of system risk under the two methods, this method measures another type of risk, namely extreme tail risk in the distribution of returns. Range volatility and the CDS premia measure less extreme risk.

6.2 Relation to regulatory interventions for $\tau = .95$

The results of the nonlinear regression of the $\Delta Covar$ estimates on the regulatory instruments appear in Table 9. We see little explanatory power of any of the instruments for bank intervention. Since all of the regressions are not significant, the partial derivatives are practically zero from one nonlinear regression to another. For mitigation contagion under extreme cases of risk, the regulatory instruments have no significant effects.

Figure 10: Maximum Values of $\Delta Covar$ with Rolling Regression Estimation

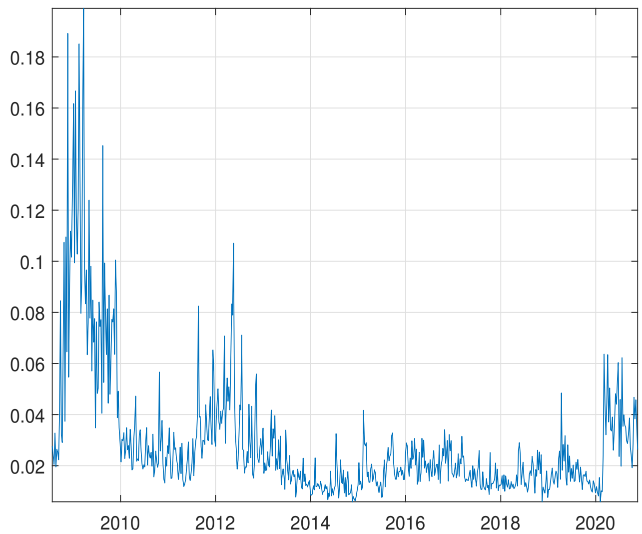


Table 8: $\Delta Covar$ Statistics and Dates of Maximum Values

Name	Max Value	Date
BAC	0.084	20-Jul-09
BBVA	0.167	19-Jan-09
BCA	0.079	18-May-09
C	0.061	24-Oct-08
CS	0.185	16-Feb-09
GS	0.098	18-May-09
JPM	0.104	26-Jan-09
MS	0.124	4-May-09
SAN	0.199	23-Mar-09
WFC	0.129	16-Mar-09

Table 9: Nonlinear Regression of $\Delta Covar$ on Regulatory Interventions

Name	RSQ	P-val	Fine Frequency	Fine Amount	BIS Bin
BAC	0.009	1.000	0.000	0.000	0.000
BBVA	0.000	1.000	0.000	0.000	0.000
BCA	0.000	1.000	0.000	0.000	0.000
C	0.001	1.000	0.000	0.000	0.000
CS	0.000	1.000	0.000	0.000	0.000
GS	0.002	1.000	0.000	0.000	0.000
JPM	0.000	1.000	0.000	0.000	0.000
MS	0.018	1.000	0.000	0.000	0.000
SAN	0.002	1.000	0.000	0.000	0.000
WFC	0.000	1.000	0.000	0.000	0.000

7 Conclusion

We have examined the rankings of ten GSIB's based on net connectedness measure of realized share-price volatility and CDS premia, as well as Conditional Value at Risk or $\Delta Covar$ measure. We found very little overlap between the first two and the last measure. Only two, SAN and BBVA, appeared among the leading banks in terms of being a source of system risk.

We also examined how the regulatory interventions affect the degree to which individual banks transmit risk to other banks or to the banking system as a whole. For each bank, we examined how individual fines and BIS classifications of that particular bank, affect its transmission of systemic risk. Under the realized volatility and CDS premia as measures, regulatory measures appear to have significant effect on the net connectedness of only a few GSIB's, such as Wells Fargo and BCA, with the BIS Bin classification having the strongest as well as dampening negative effects on net risk transmission. For the Conditional Value at Risk measure, none of the regulatory measures appeared to have significant effects on any of the GSIB's.

Our conclusion reinforces the results of Moratis and Sakellaris (2021), who argue that measures of net connectedness, easily available from market information on a daily basis, is a tool which can be implemented by regulators, and can be applied to banking networks at the regional, national and international levels. It can pinpoint bilateral dependencies as well as smaller clusters of interconnected banks within a wider network. Such adoption can only make regulatory interventions more effective tools for financial stability.

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