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Abstract

This paper empirically analyzes the determinants of systemic risk using dynamic panel data regressions, because they allow controlling for unobserved heterogeneity and omitted variables, decreasing the bias in the coefficient estimates. Additionally, it analyzes the recurrence of high systemic risk events using a duration models approach, in which the time spent in a state of financial stability is probabilistically characterized, as well as the transition probability to an unstable state, in which systemic risk is high. Moreover, it suggests that the expected duration of financial stability can be used as a leading index for systemic risk.

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1. Introduction

Financial markets are interconnected as a consequence of linkages between financial institutions, which represent an efficient risk sharing mechanism. However, financial crises arise and an important cause is the occurrence of idiosyncratic liquidity shocks affecting the financial system which, through a contagion mechanism spread across institutions throughout the same linkages that in stable periods embodies strength. Thus, systemic risk is the risk suffered by the whole financial system because the risk of individual institutions is transmitted across the system through a contagion mechanism.

Systemic risk is a cyclical phenomenon because banks are beaten by liquidity shocks that arise in response to fluctuations of the business cycle. However, a financially healthy bank should be able to resist the shocks' adverse effects, while banks which take higher risks should suffer a severe negative impact. If a bank is greatly affected by the shock, then the shock is transmitted to other banks, unleashing a contagion event. Therefore systemic risk depends on aggregate variables that affect the whole system, as well as on characteristics of each bank that makes it more or less vulnerable to shocks.

Given that systemic risk is cyclical and also depends on characteristics of each bank, then some banks would be suffering states of financial instability more frequently than others. Then, the probability of occurrence of systemic risk events can be characterized in function of both: characteristics of the economy and the banks. Based on this observation, this paper proposes to

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use a duration models approach to probabilistically characterize the time spent by a bank in a state of financial stability, as well as the transition probability to an unstable state, in which systemic risk is high (financial distress).

This paper has two objectives. In the first place to analyze the determinants of systemic risk proposed by literature, empirically verifying the effect of these variables over a measure of systemic risk. Thus, it can be determined which variables have a more important effect over systemic risk (and which variables do not have effect over systemic risk). Second, it proposes to use the expected duration of banks in a state of financial stability, conditional on the determinants of risk, as a leading index for systemic risk. An index like this would allow implementing policies to stabilize the financial system and prevent contagion events.

The database contains quarterly data of publicly traded banks in the US, during the period 1992Q1-2010Q4. This information was collected from the FDIC and Federal Reserve databases. The quarterly series for the systemic risk variable, $\Delta CoVaR$, was provided by Adrian and Brunnermeier, its original authors.

I analyzed the determinants of risk using dynamic panel data regressions because they allow controlling for unobserved heterogeneity and omitted variables, decreasing the bias in the coefficient estimates. The key assumption is that the lagged dependent variables capture the effect of omitted variables varying in time and across banks, like the number of interconnections of a bank, which could increase as the bank grows, making it risky for the system.

Then I analyzed the duration of financial stability using a Cox proportional hazard model and the determinants of systemic risk as covariates. The survivor function of a bank is constructed on the basis of the hazard rate (the Cox regression outcome), and then the expected duration is calculated.

Finally, I showed how the expected duration of financial stability of a bank could be used as a leading index for systemic risk. A regulatory body like the central bank could monitor the expected duration of stability, paying particular attention to banks with a low expected duration (or rapidly decaying expected duration) to take preventive measures, for example, injecting liquidity into troubled banks or the whole financial system (acting as a lender of last resort), avoiding the emergence of a contagion which may end affecting a larger fraction of the financial system.

The paper is organized as follows: section 2 is a brief literature review of systemic risk (mechanisms and determinants); section 3 describes the data used in the empirical analysis; section 4 describes the methodology used for identifying the determinants of systemic risk; section 5 shows the results of the estimations; section 6 describes the duration analysis methodology and shows the results of estimations; section 7 shows how the expected duration can be used as a leading index for systemic risk; section 8 summarizes the results and concludes.

2. Economics of systemic risk

This section describes some models that explain the systemic risk phenomenon, which it is defined as the risk suffered by the whole financial system because the risk of individual institutions is transmitted across the system through a contagion mechanism. The objective is to identify the mechanisms and variables that characterize systemic risk. Later these variables will be empirically tested.

Allen and Gale (2000) proposed a model to explain the financial contagion mechanism, in which banks face liquidity shocks and the cross holdings of deposits provide insurance against them; however, the linkages between banks also produce financial fragility because the shocks can spread across the system through the same interconnections. Depositors interpret signals that deliver information about the state of the business cycle, and when they receive information about an imminent recession they anticipate that banks could have financial distress, and try to withdraw their deposits causing liquidity shocks. Banks frequently face liquidity shocks, so they get insurance against them through an interbank market, holding deposits in other banks. If the shock is too big, the affected bank collapses and the other banks lose the deposits that hold in the failed bank. The contagion process starts in this way. The degree of financial fragility depends on the structure of the interbank network, that is, the number of interconnections between banks.

Alternatively, Freixas et al. (2000) propose a model in which interconnections between banks enhance the resilience of the system to get over the insolvency of a particular bank, but they are also a source of contagion. This model is similar to Allen and Galle model, but the emphasis is in "where" the shocks arise instead on "when". They also give fundamentals to the "too-big-to-fail" policy, that is, the concern for stabilizing banks that in case of failing would produce a high systemic risk and contagion, since they are playing a key role in the interbank network. Nier et al. (2008) analyze this network theories about contagion using simulated banking systems.

Brunnermeier and Sannikov (2009) propose a macroeconomic model with financial sector, in which financial stability depends on the business cycle, but the financial sector activity, in turn, amplifies the business cycles. The risk is endogenous because the investors assume high leverage ratios in stable periods since prices rise endogenously, so their assets value rises too. In the same way they choose their capital ratios to be able to withstand reasonable losses. However, part of the risk is exogenous, in the form of shocks affecting the financial system. If shocks are too large, the investors will not be able to withstand losses, which will translate into a fall in prices. Then the leverage ratios chosen by investors will growth endogenously, intensifying the instability in the financial system. Paradoxically, the low endogenous risk in stable periods makes the financial system vulnerable to volatility crises, phenomenon the authors call volatility paradox. Brunnermeier and Pedersen (2009) also propose a model relating economic cycle and financial stability, and Adrian and Shin (2010) provide empirical evidence for this phenomenon.

Summarizing, the determinants identified on the basis of these works are:

Business cycle variables, that are signals about the state of the business cycle, which modify the depositors' expectations. When signals are negative depositors expect that the banks will not be able to honor its debt, and respond withdrawing their deposits. When many depositors act in the same way, this situation turns into a liquidity shock affecting the bank or the whole financial system.

Liquidity, since banks are intrinsically fragile due to its function of supplying liquidity to the economy, which is demanded by risk-averse depositors. Banks receive liquid deposits that can be withdrawn when depositors wish, while invest in illiquid long term assets with a higher return but when are liquidated early produce losses. A bank invests in a portfolio of short and long term maturity assets, according to its estimation about the aggregate risk (fraction of depositors who withdraw in the short and long term). A liquidity shock makes that an unexpected number of depositors wish to withdraw their deposits, producing losses in the bank because it has to liquidate the long term assets at discount to satisfy the unexpected demand for liquidity. If the shock is big enough the bank goes bankrupt, and all its assets are liquidated at discount, with the consequence that other banks with deposits in the distressed one suffer losses too, situation that can trigger a contagion process. If a bank has good liquidity ratios, that is, if the bank has enough short term assets to satisfy any unexpected demand, it will be less systemically risky.

Leverage, as Brunnermeier and Sannikov (2009) point out that investors (including banks) choose leverage ratios endogenously during stable periods of growth due to upward distortions in assets prices, that in turn distort the leverage ratios. The larger leverage makes the banks prone to instability periods, because their returns become volatile, so they are exposed to financial insolvency. In deceleration or recessive periods this effect is larger because the fall in prices endogenously makes grow the leverage ratios.

Size, since financial contagion is produced because the losses suffered by a bank spread to other banks through the interconnections between them. A larger bank produces a larger loss in the financial system, because the amount of assets liquidated at discount is larger, and also because the contagion is wider, since a larger bank should have a large number of interconnections with other banks. Regarding size and interconnections, authors like Freixas et al. (2000) and Chan-Lau (2010) argue that more important than the size of a bank is how interconnected is.

The *number of interconnections of a bank* is an important determinant of systemic risk, since when a bank with a large number of interconnections is affected by a liquidity shock, it will transmit only small shocks to each of the banks in its structure, dissipating the shock's negative effect. However, if the shock is big enough the initial spread could turn into a contagion to a large number of banks.

3. Data

3.1. Systemic risk variable

There are alternative methods to measure systemic risk. For example, Segoviano and Goodhart (2009) define the banking system as a portfolio of banks and infer the multivariate density of the system using individual risk probabilities as exogenous variables. Then they estimate financial stability measures, like the joint probability of financial distress or conditional probabilities of distress. Chan-Lau (2010) describes a method to analyze the risk arising from direct exposures related with the balance sheets of institutions. This method allows analyzing how the shocks affecting an institution spread across the banking system, using counterfactual simulations. Then he obtains indexes like the total bankruptcies (or the total capital losses) induced by the bankruptcy of a particular institution. Another papers addressing network analysis literature are Nier et al. (2008) and Upper (2011). Huang et al. (2012) propose a systemic risk indicator measured by the price of insurance against systemic financial distress, based on credit default swap (CDS) prices. Billio et al. (2012) propose several econometric measures of connectedness based on principal-components analysis and Granger-causality networks.

I chose to use the measure of systemic risk proposed by Adrian and Brunnermeier (2009). They suggest a measure called $\Delta CoVaR$, that captures the marginal contribution of a particular institution i to overall systemic risk. The $\Delta CoVaR^{j|i}$, is the difference between the financial system VaR (institution j) conditional to an institution i being in distress (5% VaR), and the financial system VaR conditional to the same institution i in the median state of its return distribution (50% VaR). The authors also interpret the $\Delta CoVaR$ as the difference between the maximum percentage loss in the system assets value when a particular institution is in the median state of returns (50%) and when it is in an extreme state (5%)[1].

An advantage of this measure is that different measures of risk can be used as exogenous variable (not necessarily the value at risk, VaR), which is good because in many countries the quality and/or quantity of available data is limited. Besides, many measures can be constructed, like the contribution of a particular institution to systemic risk, the contribution of an institution to another institution risk, and the contribution of the system to an institution risk. For example, Wong and Fong (2011) estimate $CoVaR$ to study the interconnections between the financial systems of 11 Asia-Pacific economies, and Gauthier et al. (2012) estimate systemic risk exposures for the Canadian banking system.

The quarterly series for $5\%\Delta CoVaR$ was provided by Adrian and Brunnermeier, the original authors. The sample has 1,194 financial institutions and 100 quarters, between 1986Q1 and 2012Q4. All of the institutions are publicly traded in capital markets. Figure 1 shows this series and table 1 displays its descriptive statistics.

Table 2 shows the recessive periods in the US during the sample period. A recessive period is the interval between the highest and the lowest point of a cycle. Figure 1 shows these intervals in shaded areas. Two of three recessions can be associated with periods of high systemic risk, so systemic risk would

[1]The $\Delta CoVaR$ is estimated using quantile regressions, a method introduced by Koenker and Hallock (2001)

Table 1: DeltaCoVaR(5)

Mean	0.0010
Std.Deviation	0.0003
5th percentile	0.0007
25th percentile	0.0008
Median	0.0009
75th percentile	0.0012
95th percentile	0.0015

be countercyclical, it rises in recessive periods. The exception is the second recessive period, between 2001Q1 and 2001Q4, since there is a decrease of systemic risk during the interval. Respecting the historical context, the first recession (1990Q2-1991Q1) was a consequence of the 1987 financial crisis. Even though the financial markets recovered quickly, banks were too beaten and recovered slowly, so the credit supply of the economy was affected. The second recession (2001Q1-2001Q4) is the period after the Nasdaq crisis (dot-com bubble). The Nasdaq Stock Market reached its maximum market value in March 2000, and then steadily declined for 18 months. The third recession (2007Q4-2009Q2) started as a result of the bursting of the real estate bubble during 2007.

Table 2: Recessions in the US (Source: NBER)

Highest point	Lowest point
1990Q2	1991Q1
2001Q1	2001Q4
2007Q4	2009Q2

Table 3: Financial crises

Crisis	Period
Black monday	1987Q3
Oil price shock	1990Q3
Asian financial crisis	1997Q3
Nasdaq crisis	2000Q1
Bankruptcy of Lehman Brothers	2008Q3

Table 3 shows the dates of financial crises during the sample period, and figure 1 shows its dates of occurrence through vertical lines. The first one was the “Black Monday”, when stocks markets around the world crashed one by one through a contagion mechanism that began in Hong Kong. The next was the Asian financial crisis, in 1997, affecting the price of currencies, and then the Nasdaq crisis, after the bursting of the "dot-com bubble" in 2000. Finally the crisis associated to the bankruptcy of Lehman Brothers, the fourth largest investment bank in the US in that moment, and the largest bankruptcy in the US history. Systemic risk appears to rise before and mainly after financial crises. The relation between financial crises and systemic risk is more evident than the relation with recessions, but it is not causal because systemic risk grows since before the start of a crisis. However, the occurrence of a crisis would have an amplifying effect over the risk levels.

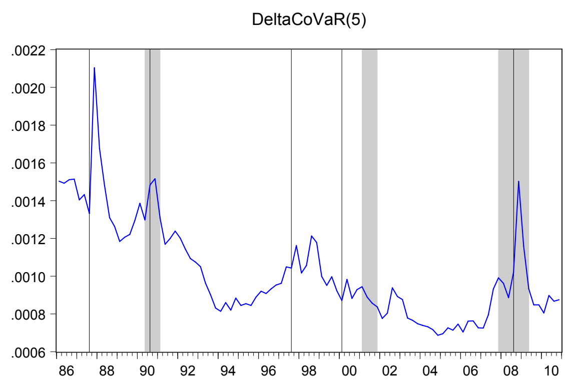

Figure 1: DeltaCoVaR(5) quarterly means series
Shaded areas: recessive periods
Vertical lines: financial crises

The relation between recessive periods and financial crisis is more complex than it seems. It would appear that financial crises are random events, as prior theories before Allen and Gale (2000) suggested, and that financial crises produce recessions and not the opposite. This relation can be clarified using the model of Brunnermeier and Sannikov (2009), in which the financial system stability depends on the economic cycle, but the cycles in turn are amplified by the financial sector activity. For example, if investors observe a deceleration they anticipate a recession, reacting immediately and disproportionately, causing a financial crisis that make the deceleration worse, finally ending in recession.

3.2. Determinants of systemic risk variables

The variables must be the ones that the theory suggests are related to systemic risk. I use specific variables for each of the identified determinants, excepting for the interconnections structure of the banks (how much diversified are the assets and liabilities of the banks). All these variables were collected from the FDIC and Federal Reserve databases.

Loan to deposit ratio. Illiquidity index. The higher the ratio the highest the iliquidity of the bank, because assets (illiquid, long term) would be much more than liabilities (liquid, short term), so the banks might not have enough liquidity to cover any unforeseen fund requirements, being vulnerable to liquidity shocks. The relation with systemic risk should be positive. This variable is abbreviated as *illiquidity*.

Tier 1 capital ratio. An inverse leverage index that can be understood as a financial strength index. It is the tier 1 capital as a percent of risk-weighted assets. Tier 1 capital includes: common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. Since this ratio is an inverse leverage index, the relation with systemic risk should be negative, because the higher the ratio the more stable the banks returns and the less prone the banks to financial insolvency. This variable is abbreviated as *strength index*.

Average assets (ln). This variable is a measure of size. It is the average between the current total assets and the previous. The relation with systemic risk should be positive, because the larger the bank the larger the losses for the system if the bank goes bankrupt. Besides, banks that have grown also have developed a greater number of interconnections, so can transmit risk to a larger number of banks.

Leading index. Business cycle variable constructed by the Federal Reserve Bank of Philadelphia. The leading index predicts the six month growth rate of the coincident index, which in turn is a variable that summarizes current economic conditions in a single statistic. A positive change (growth) is a positive signal for depositors, who will be less prone to react generating liquidity shocks, and vice versa. The relation with systemic risk should be negative.

3.3. Control variables

Control variables are used to reduce the omitted variable bias and for establishing more appropriately if there is a causal effect of determinants over the dependent variable. If the regressions have no other variables that could have some effect over the dependent variable, there will be a bias (positive or negative) in the coefficients estimates for determinants. I use the following control variables:

Noninterest income to assets. Income derived from bank services and sources other than interest bearing assets as a percent of average assets. In general are incomes from fees, and allow the bank to assure liquidity when the default rates are increased. The relation with systemic risk should be negative.

Return on assets, ROA. Net income after taxes as a percent of average total assets. Financial theory suggests a positive relation between risk and return: the higher the return the higher the risk, but (in the medium term) more profitable banks should have an easier access to financing when they require it. The relation with systemic risk is not clear.

Credit loss provision to net charge-offs. Provision for possible credit and allocated transfer risk as a percent of net charge-offs. Provision is the amount saved for expected losses and net charge-offs is the amount actually lost. If the ratio is high the effective losses would have been less than the expected. The relation with systemic risk should be negative, since it is a good signal to depositors.

Change in the S&P500. Percentage change in the S&P500 index from the previous period. It should be a positive signal for depositors, since this index would reflect the investors' expectations about the economy. However, it also could imply deviating funds from the banking system to capital markets. The relation with systemic risk is not clear.

Table 4: Descriptive statistics

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
DeltaCoVaR(5)	35160	0.0009	0.0010	-0.0049	0.0101
Iliquidity	28150	0.9004	0.2287	0.0000	4.8298
Strength index	28156	0.1325	0.1328	-0.0266	10.0030
ln(Size)	28156	13.8928	1.6360	7.8984	21.3607
Leading index	33179	0.9079	1.0142	-2.8900	2.3300
Noninterest income/assets	28156	0.0299	0.0160	-0.6351	0.4769
ROA	28156	0.0082	0.0144	-0.4758	0.1650
Provision/net charge-offs	27146	2.4279	44.6633	-3,615	1,754
DeltaSP500	33179	1.3479	6.7475	-27.2000	12.9000

Table 4 shows the descriptive statistics for the systemic risk variable, determinants and control variables.

4. Methodology: Identifying the determinants of systemic risk

I used dynamic panel data regressions because they allow controlling for unobserved heterogeneity and omitted variables, decreasing the bias in the coefficient estimates. The generic model is:

$$y_{it} = \alpha_i + \phi_1 y_{it-1} + ... + \phi_p y_{it-p} + x'_{it}\beta + \varepsilon_{it}$$

Where the dependent variable y_{it} is the systemic risk measure $\Delta CoVaR_{it}$; α_i is a fixed effect, that captures the effect of omitted variables that are assumed constant over time but not across banks, like the bank's management style (managers' degree of risk aversion). The lagged dependent variables capture the effect of omitted variables varying in time and across banks, as Angrist and Pischke (2008) explain. For example, the number of interconnections of a bank, which could increase as the bank grows, making it risky for the system; x_{it} are the determinants and control variables: the observable characteristics.

The estimation of this model is inconsistent because the introduction of the lagged dependent variable, so the right strategy to estimate the coefficients is using the first differences model and the Arellano-Bond estimator.

$$\Delta y_{it} = \phi_1 \Delta y_{it-1} + ... + \phi_p \Delta y_{it-p} + \Delta x'_{it}\beta + \Delta\varepsilon_{it}$$

Given that T is large, many instruments are available, so the Arellano-Bond estimator was implemented using the two-step GMM estimator, given that the model is overidentified and this method allows a more efficient estimation.The determinants and control variables were treated as exogenous, so they were used as instruments for themselves. The number of instruments for the lagged dependent variables of each regression was chosen using a test of over-identifying restrictions (Sargan Test). The number of lags for the dependent variable was chosen to assure that ε_{it} is serially uncorrelated.

I analyze two regressions: a short one, which includes only the determinant variables of systemic risk, and a long one, which also includes control variables. In this way the causality of the relations encountered will be established more robustly, since the short regression estimation could be biased (omitted variable bias). Additionally, I use clustered robust standard errors.

The dependent variable is measured on a scale that is difficult to interpret, because its small values (in percentage points, with a mean equal to 0.0010) are reflected in small coefficients. It seems that the estimates are not economically significant. To address this problem I also show the results of regressions with standardized variables (within each group). An advantage of standardization is that regardless the measurement units of the original variables, coefficients are comparable. Therefore, the magnitude of coefficients points out what variables have more importance over systemic risk determination.

5. Results

Table 5 shows the estimation results. Columns (1) and (2) show the results for the regression using the original variables. The coefficients of the lagged dependent variables sum 0.5351 in the short regression and 0.5568 in the long regression, showing that a great fraction of the contemporaneous risk depends on past risk. The number of interconnections of a bank is a relevant omitted variable varying in time, so its effect could be being reflected in these coefficients.

There is a positive relation between systemic risk and illiquidity, only significant in the long regression. A greater strength index (less leverage) is associated negatively with systemic risk, but its effect is only significant at the 10% level in the long regression.

The size effect over systemic risk is almost zero in both regressions, probably because the scale of measurement of the dependent variable, so this relation will be better analyzed using the regressions with standardized variables. The same is valid for the leading index, since the results do not allow getting sound conclusions.

Among the control variables, only ROA and deltaSP500 were significant at the 1% level. The effect of ROA over systemic risk is negative and the DeltaSP500 effect is positive but close to zero.

Columns (3) and (4) show the results for the regressions using standardized variables. The coefficients of the lagged dependent variables sum 0.5118 in the short regression and 0.5347 in the long regression, nearly the same as the previous results. There is a positive relation between systemic risk and illiquidity, significant at the 1% level in both regressions, and a negative

Table 5: Results: dynamic panel estimates
Columns (1) and (2): original variables
Columns (3) and (4): standardized variables
Dependent variable: $DeltaCoVaR(5)_{it}$

	(1)	**(2)**	**(3)**	**(4)**
L1.DeltaCoVaR(5)	0.5363***	0.5172***	0.4402***	0.4034***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
L2.DeltaCoVaR(5)	-0.1631***	-0.1141***	-0.0569***	-0.0096
	(0.0000)	(0.0000)	(0.0000)	(0.2920)
L3.DeltaCoVaR(5)	0.1619***	0.1537***	0.1285***	0.1409***
	(0.0030)	(0.0000)	(0.0000)	(0.0000)
Iliquidity	0.0002	0.0002***	0.1238***	0.1082***
	(0.1480)	(0.0000)	(0.0000)	(0.0000)
Strength index	-0.0001	-0.0001*	-0.0331**	-0.0481***
	(0.6070)	(0.0870)	(0.0500)	(0.0050)
ln(Size)	-0.0001*	0.0000**	-0.1083***	-0.0917***
	(0.0810)	(0.0110)	(0.0000)	(0.0010)
Leading index	-0.0001***	0.0000***	-0.2517***	-0.0154
	(0.0000)	(0.0050)	(0.0000)	(0.2580)
Noninterest income/assets		-0.0005		0.0006
		(0.1150)		(0.9650)
ROA		-0.0006***		-0.0215*
		(0.0040)		(0.0590)
Provision/net charge-offs		0.0000		0.0109*
		(0.6250)		(0.0820)
DeltaSP500		0.0000***		-0.3090***
		(0.0000)		(0.0000)
Constant	0.0011**	0.0008***	-0.0066**	0.0022
	(0.0480)	(0.0010)	(0.0390)	(0.5640)
Obs	25,780	24,615	25,764	24,606
Banks	589	586	587	584
Wald chi2	1095.51	5974.53	6337.27	4737.73
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Number of instruments	605	534	605	609

p values in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

relation with the strength index, significant at 5% and 1% level in the short and long regression, respectively[2].

The size effect over systemic risk is negative and significant in both regressions, the opposite of the expected, however, some authors like Freixas et al. (2000) and Chan-Lau (2010) suggest that more important than size (too-big-to-fail) is how interconnected is a bank (too-connected-to-fail), so the results obtained for this variable would be explained by the inclusion of the lagged dependent variables, which capture in part the effect of interconnections, that are assumed related with size. The negative effect encountered for size could be explained due to the fact that larger institutions can get funding easier, as well as can bear larger losses for longer periods than smaller institutions.

On the other hand, a positive relation between size and systemic risk could be expected, due to the way the dependent variable is constructed. Financial system VaR (and $\Delta CoVaR$) is constructed on the basis of the distribution of returns on the total market-valued financial assets, which in turn is generated by taking the average market-valued asset returns of each bank, weighted by the lagged market-valued total assets. However, Adrian and Brunnermeier (2009) argue that $\Delta CoVaR$ is not always higher for larger banks, since also small banks could have high levels of systemic risk when they are banks acting like a herd, that is, when many small banks of similar characteristics are affected by some common factor that simultaneously causes losses in all the banks (thus the loss of the system is large). For example, a crisis in the real estate sector will affect simultaneously all the banks financing the sector.

The leading index variable has a negative effect over systemic risk, because an increase in the variable's value is a good signal for investors. The effect is significant at the 1% level only in the short regression. In the long regression the leading index has not a significant effect due to the inclusion of the DeltaSP500 variable, which would be more important than the leading index in the creation of depositors' expectations.

Among the control variables, ROA has a negative and significant effect at the 10% level over systemic risk; Provision/net charge-offs has a negative effect, as expected, significant at the 10% level; and finally the DeltaSP500

[2]The differences in significance are explained by the way of standardization, within each group (alternatively it could have been performed using pooled data) and by the number of instruments used in each regression, chosen according to the Sargan test.

variable was significant at the 1% level. The effect is negative, because an increase in the index should be a positive signal for depositors, since this index would reflect in part the investors' expectations about the economy, so the systemic risk should be decreasing.

The most important determinant in coefficient magnitude was the lagged dependent variable followed by DeltaSP500 (which would be replacing the leading index variable in its role of business cycle signal), the iliquidity variable, size and finally the strength index.

In conclusion, the results obtained from regressions depend on the type of structure assumed for the omitted variables. An important variable like the interconnections structure of a bank is omitted, however, since the dependent variable is the risk of the system caused by an individual institution, the variations in the interconnections structure of each institution (variation over time and across banks) could be captured using lags of the dependent variable, so the dynamic panel data model should deliver reliable results. The relations estimated were consistent with the theory, so the model must be correctly specified.

6. Duration of the financial stability

Using the systemic risk variable and its determinants, it is possible to characterize the duration of financial stability. For that purpose, the first step is defining financial stability and instability states, as a function of the risk variable. The unstable state is a high risk state (financial distress), when systemic risk is greater than an arbitrary limit, while the stable state is a state in which risk is less than the limit. I have established two limits: (1) the mean of the quarterly averages series (0.0010), (2) 75th percentile of the quarterly averages distribution (0.0012).

Table 6 shows the means for the variables in each state defined by limit 1, the differences between means, and tests for significance of the differences. Table 7 shows the same information for the states defined by limit 2. The results of the tests were the same in both tables. The systemic risk is higher in the unstable state, by definition. The illiquidity mean is higher in the stable state, the opposite of the expected. There are no significant differences in the strength index. The banks in the instability state are significantly larger. The leading index is higher in the stable state, so there are better economic conditions in stability periods. The Noninterest income to assets variable that is a measure of liquidity, is higher in the instable state, the opposite of the expected. ROA is higher in the instability state. There

Table 6: Means by state (limit 1) and Test for differences

Variable	**Instability**	**Stability**	**Difference**	**S.E.(diff.)**	**t-test**
DeltaCoVaR(5)	0.0018	0.0003	0.0015***	0.0000	206.0357
Iliquidity	0.8925	0.9048	-0.0123***	0.0029	-4.2874
Strength index	0.1320	0.1327	-0.0007	0.0020	-0.3439
ln(Size)	14.5362	13.5380	0.9982***	0.0218	45.8051
Leading index	0.8758	0.9274	-0.0515***	0.0118	-4.3741
N.I. income/assets	0.0308	0.0294	0.0013***	0.0002	6.0632
ROA	0.0092	0.0077	0.0015***	0.0002	8.1125
Prov./net charge-offs	2.2144	2.5467	-0.3323	0.6338	-0.5243
DeltaSP500	1.0997	1.4992	-0.3995***	0.0783	-5.1027

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Means by state (limit 2) and Test for differences

Variable	**Instability**	**Stability**	**Difference**	**S.E.(diff.)**	**t-test**
DeltaCoVaR(5)	0.0020	0.0004	0.0016***	0.0000	202.8072
Iliquidity	0.8931	0.9035	-0.0104***	0.0030	-3.4171
Strength index	0.1323	0.1325	-0.0002	0.0024	-0.0762
ln(Size)	14.6732	13.5684	1.1048***	0.0241	45.8788
Leading index	0.8747	0.9233	-0.0486***	0.0125	-3.8952
N.I. income/assets	0.0308	0.0295	0.0013***	0.0002	5.2649
ROA	0.0093	0.0078	0.0016***	0.0002	8.2456
Prov./net charge-offs	2.4180	2.4321	-0.0141	0.6821	-0.0206
DeltaSP500	1.0504	1.4859	-0.4355***	0.0829	-5.2566

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

are no differences in the Provision/Net charge-offs variable, and finally, the DeltaSP500 is higher in the stable state, reflecting better expectations about the economy in stable periods.

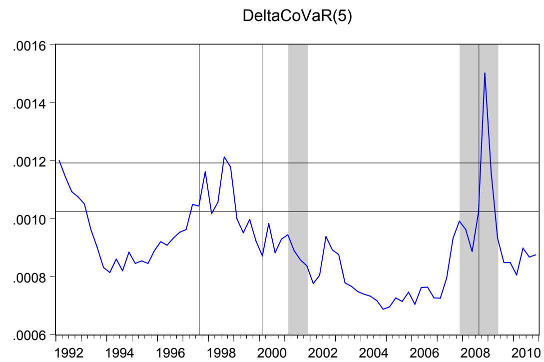

Figure 2: Sample division in states
Superior horizontal line: 75th percentile of quarterly averages distribution (0.0012)
Inferior horizontal line: Mean of quarterly averages (0.0010)
Shaded areas: recessive periods
Vertical lines: financial crises

Figure 2 shows the division between states through horizontal lines. Banks alternate stability and instability periods, so once the origin of each stable period is identified, the *duration* is the number of periods between the origin of a stable period and the period in which transition to the unstable period occurs. In this period the bank is at risk (time at risk) since there is the possibility of suffering a transition to the unstable state[3]. Next I describe some basic concepts about this methodology as well as the Cox proportional hazard model, which allows characterizing the duration of financial stability periods as a function of risk determinants[4].

The *duration* in a state is a nonnegative random variable, which measures

[3]To clarify nomenclature: the variable of interest is the *duration* or permanence in a state before moving to another state, that is, the time spent in a given state. A *state* is a classification of an individual at a point in time, and *transition* is the movement from one state to another.

[4]The methodology description is based on Kiefer (1988) and Cameron and Trivedi (2005).

periods of time, and is denoted T. The cumulative distribution function of T is denoted $F(t)$ and the density function is denoted $f(t)$. Then the probability that the duration is less than t is:

$$\begin{aligned} F(t) &= Pr(T \leq t) \\ &= \int_0^t f(s)ds \end{aligned}$$

In addition, the *survivor function* is the probability that duration equals or exceeds t:

$$\begin{aligned} S(t) &= Pr(T > t) \\ &= 1 - F(t) \end{aligned}$$

The *hazard function* is the instantaneous probability of leaving a state conditional on survival to time t. In other words, it is the instantaneous probability of moving to a financial instability state given having been t periods in the stable state:

$$\begin{aligned} \lambda(t) &= \lim_{dt \to 0} \frac{Pr(t \leq T < t + dt \mid T \geq t)}{dt} \\ &= \frac{f(t)}{S(t)} \end{aligned}$$

There are two concepts of time in this type of models. The first is *date*, or how time is measured in the database (quarters), and the second one is the time under analysis or *time at risk*, which is denoted t. If all durations begin in the same period (same origin) both concepts would be the same, and durations would be being measured in real time, however, durations in this paper are being measured from different origins, so the relevant concept of time is t, the time at risk, and not real time.

In the *Cox proportional hazard model* interest is in the conditional hazard rate, $\lambda(t \mid x)$, unlike other regressions approaches in which interest is in the conditional mean function, $E(T \mid x)$. This model assumes that the hazard rate is heterogeneous: vary across institutions, but it is proportional to a baseline hazard. Therefore, the conditional hazard rate can be factored into separate functions:

$$\lambda(t \mid \mathbf{x}, \beta) = \lambda_0(t) \exp(\mathbf{x}, \beta)$$

where $\lambda_0(t)$ is the *baseline hazard*, which is function of t (time at risk) alone, while $\exp(\mathbf{x}, \beta)$ is function of $\mathbf{x}$ alone (the regressors: the determinants of systemic risk). All conditional hazard functions are proportional to the baseline hazard, with a scale factor $\exp(\mathbf{x}, \beta)$ that is not an explicit function of t. In practice, the baseline hazard is not estimated but can be recovered after estimation of β, evaluating the hazard function at $\mathbf{x} = 0$.

The original sample includes a total of 35,160 observations (720 institutions), between 1986Q1 and 2010Q4, however, it only includes regressors since 1992Q1. Besides, in the duration analysis only matters transition from the stable state to the unstable one, so the observations in the unstable state are irrelevant for estimation, implying that about a 40% of the sample is not used.

This type of models allows using censored durations, that is, durations which origin or end is unknown. This is not a problem since the likelihood function considers censoring. On the other hand, it uses an identification variable for durations rather than banks, but the robust errors are clustered by banks, the original identification variable.

Table 6 shows the results of estimations. Columns (1) and (2) show the results for regressions with risk limit equal to the mean of quarterly averages, while columns (3) and (4) show the results for regressions with risk limit equal to the 75th percentile of quarterly averages distribution. It must be noted that when the limit of risk is higher (75th percentile) fewer observations and banks are excluded of the sample but the total sum of durations and transitions is smaller.

For both states definitions, coefficients for variables illiquidity and strength index had the expected signs (relations), but are not significant. The hazard rate is positively related with size and negatively related with the leading index. Both relations are significant at the 1% level. Saying that a variable has a positive effect over the hazard rate is equivalent to say that it increases the transition probability to an instability state or that it produces a fall in the survivor function, and vice versa. So banks with larger size have a higher transition probability to an instability state, and when the leading index is positive, indicating good economic conditions, the transition probability to an instability state drops.

The differences in coefficients magnitude are small when comparing the short and long regressions, so the bias of estimates must be small too. Unlike the determinants analysis, the DeltaSP500 had not a significant effect over transition probability, while the leading index was a better measure of expectations.

Table 8: Results: Cox proportional hazard model
Columns (1) and (2): risk limit is the mean of quarterly averages
Columns (3) and (4): risk limit is the 75th percentile of quarterly averages distribution
Dependent variable: time at risk

	(1)	**(2)**	**(3)**	**(4)**
Iliquidity	0.2214	0.2082	0.1523	0.1269
	(0.2330)	(0.2700)	(0.4500)	(0.5490)
Strength index	-1.0481	-1.5798	-0.0276	-0.8600
	(0.3140)	(0.2060)	(0.9760)	(0.4810)
ln(Size)	0.20171***	0.20251***	0.21271***	0.23061***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Leading index	-0.12201***	-0.13331***	-0.22121***	-0.21501***
	(0.0010)	(0.0000)	(0.0000)	(0.0000)
Noninterest income/assets		-1.5641		1.9447
		(0.7260)		(0.6570)
ROA		5.41731*		6.08781*
		(0.0860)		(0.0730)
Provision/net charge-offs		0.0013		0.00221**
		(0.1580)		(0.0460)
DeltaSP500		0.0000		-0.0046
		(0.9940)		(0.5130)
Durations	1027	1004	952	932
Transitions	642	613	529	499
Banks	467	466	500	500
N	17,740	17,045	19,446	18,686
Wald	84.02	91.90	95.38	102.87
Prob > chi2	0.0000	0.0000	0.0000	0.0000
ln L	-4,100.49	-3,878.54	-3,326.55	-3,103.41

p values in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7. Expected duration as a leading index for systemic risk

The following analysis illustrates the effect of determinants over the expected duration of a bank, using the results of regression (1). The objective is to analyze the effect of a negative change in the leading index, which should be understood by depositors as a negative signal about business cycle, and should generate liquidity shocks over the banks, increasing systemic risk.

The survivor function of a bank can be constructed on the basis of the hazard rate, and then calculate the expected duration in financial stability. The concept to analyze is the *expected future lifetime*, that is the expected value of future lifetime. The probability of transition at time $t + t_0$ given survival until time t_0 is:

$$Pr\,(T \leq t_0 + t \mid T > t_0) = \frac{Pr\,(t_0 < T \leq t_0 + t)}{S(t_0)} = \frac{F(t_0 + t) - F(t_0)}{S(t_0)}$$

The probability density of future lifetime is:

$$\frac{d}{dt}\frac{F(t_0 + t) - F(t_0)}{S(t_0)} = \frac{f(t_0 + t)}{S(t_0)}$$

So the expected future lifetime is:

$$\frac{1}{S(t_0)}\int_0^\infty tf(t + t_0)dt = \frac{1}{S(t_0)}\int_0^\infty S(t)dt$$

When $t_0 = 0$, that is when a stability state is starting, the expression is the *expected lifetime*, or the stability state expected duration:

$$\int_0^\infty tf(t)dt = \int_0^\infty S(t)dt$$

For a bank with all its determinants in the mean of the sample, the expected duration is 33 quarters (survivor 1, figure 3). The mean for the leadix index is 0.92, which is a good economic condition. If the leading index falls up to -0.50, reflecting a bad economic condition, the expected duration falls until 27 quarters (survivor 2, figure 3). The survivor function depends on banks characteristics, so there is one different survivor function for each bank, and if the characteristics (determinants) change the survivor function changes too. The expected survivor is conditional on time at risk, so the expected values are conditional in both: characteristics of banks and time at risk.

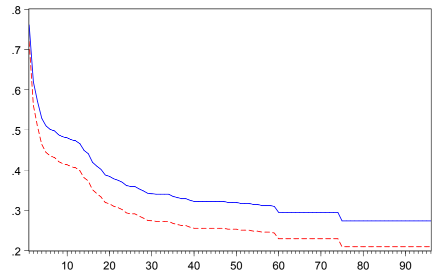

Figure 3: Survivor function
Change in the survivor function when the leading index falls
Solid line: Survivor 1; Leading index = 0.92
Dashed line: Survivor 2; Leading index = -0.50

The expected duration measures the expected number of periods until the bank experiments a transition to an instable state. In others word, when the bank reaches a level of systemically dangerous risk (which has been defined previously).

Table 9 shows the expected duration for different starting periods, t_0. When $t_0 = 0$, the result is the *expected duration*. When $t_0 > 0$ the result is the *expected future duration*, the expected duration conditional on survival until time t_0.

For a bank that has survived 10 periods and is having all its determinants in the mean of the sample, the expected future duration is 69 quarters (survivor 1, figure 3). If the leading index falls as before, the expected duration falls until 65 quarters (survivor 2, figure 3).

A regulatory body like the central bank could monitor the banks expected duration of financial stability, paying particular attention to banks which expected duration is too low (or rapidly falling period to period) to take preventive measures, for example, injecting liquidity to banks in troubles or to the system as a whole (as a lender of last resort), thus avoiding that the spread of a shock affecting a particular bank could turn into financial contagion, that in turn could affect a larger share of the financial system.

Finally, I must point out that this probability model is a reduced-form model, which implies that each time a policy is executed the structural parameters of the model changes, but the reduced-form model does not capture

Table 9: Expected durations
Leadix = Leading Index

	Leadix1 = 0.92	Leadix2 = -0.50		
t_0	$E(t \mid T > t\_0)$	$E(t \mid T > t\_0)$	Δ	$\%\Delta$
0	33.1418	26.8348	6.3070	0.2350
1	43.5268	37.2696	6.2572	0.1679
2	53.4938	47.7820	5.7118	0.1195
3	58.1433	52.8303	5.3130	0.1006
4	62.6916	57.8495	4.8420	0.0837
5	64.9955	60.4210	4.5745	0.0757
6	66.1350	61.6998	4.4352	0.0719
7	66.5989	62.2218	4.3771	0.0703
8	67.9561	63.7530	4.2031	0.0659
9	68.6465	64.5343	4.1122	0.0637
10	69.0006	64.9357	4.0649	0.0626

the policy structural effect, so must be re-estimated (Lucas critique). An example is the moral hazard problem that arises when the central bank acts rescuing banks in troubles to avoid the financial contagion. Since banks know that will be rescued by the central bank if they are facing problems, then respond taking a larger amount of risk, because they will receive the profits but not the costs of the risk, which will be assumed by the central bank. Concerning this problem authors like Freixas et al. (2000) and Stern and Feldman (2004) argue in favor of a bail-out policy, since they indicate that the cost of financial contagion (in economic welfare) is greater than the cost of moral hazard.

8. Conclusions

Summarizing, I analyzed the determinants of risk using dynamic panel data regressions because they allow controlling for unobserved heterogeneity and omitted variables, decreasing the bias in the coefficient estimates. The key assumption is that the lagged dependent variables capture the effect of omitted variables varying in time and across banks, like the number of interconnections of a bank, which could increase as the bank grows, making it risky for the system.

The results obtained from regressions were consistent with theory, so the model must be correctly specified. The most important determinant in coefficient magnitude was the lagged dependent variable (positive effect over systemic risk) followed by deltaSP500 (negative effect; it acts as a business cycle signal), the iliquidity variable (positive effects), size (negative effect) and finally the strength index (negative effect).

The size effect over systemic risk was negative and significant, the opposite of the expected, however, some authors like Freixas et al. (2000) and Chan-Lau (2010) suggest that more important than size (too-big-to-fail) is how interconnected is a bank (too-connected-to-fail), so the results obtained for this variable would be explained by the inclusion of the lagged dependent variables, which capture in part the effect of interconnections, which are assumed related with size. The negative effect encountered for size could be explained due to the fact that larger institutions can get funding easier, as well as can bear larger losses for longer periods than smaller institutions.

The duration analysis of financial stability revealed that the determinants of systemic risk play the same role in the duration of stability states, but the significant variables were only the size of a bank (which is related with the number of interconnections), and the business cycle variable, acting through depositors' expectations. Because the business cycle variables play a fundamental role in stability duration, the central bank effort for stabilizing the business cycle would have an important effect over the cycle of financial stability/instability.

The survivor function of a bank is constructed on the basis of the hazard rate, and then the expected duration is calculated. A financial regulator like the central bank could monitor the expected duration of stability, paying particular attention to banks with a low expected duration (or rapidly decaying expected duration) to take preventive measures, for example, injecting liquidity into troubled banks or the whole financial system (acting as a lender of last resort), avoiding the emergence of a contagion which may end affecting a larger fraction of the financial system. Consequently, the expected duration of financial stability of an institution could be a leading index for systemic risk.

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