Applying *CoVaR* to measure systemic market risk: the Colombian case

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Introduction

Negative shocks suffered by individual financial institutions can easily propagate and affect other entities. Due to this, measuring and analyzing the phenomena derived from systemic risk has been a common interest among policy makers. Moreover, since the recent financial crisis, this analysis has gained even more importance.

Systemic risk may not be analyzed only by using individual risk measurements of institutions. Herding behavior by financial entities may cause a high exposure to negative systemic events, even if individually all institutions have low risk measurements. Additionally, the risk assumed by a systemic institution may cause negative spillovers not internalized in risk requirements. To deal with these issues, several papers have approached systemic risk from different perspectives, according to what authors perceive is more relevant to their analysis.

For Rochet and Tirole (1996) systemic risk is materialized when a bank's economic distress propagates to other economic agents linked to that bank through financial transactions. This paper studies whether the flexibility offered by decentralized interbank transactions can be maintained, while the corresponding financial authority can be protected against undesired rescue operations. If not, centralizing interbank systems would be more efficient in terms of liquidity allocation and prudential control. In particular, the authors analyze the "too big to fail" policy: proper authorities bail out a bank with short positions in the interbank market because the bank's distress may affect solvent lending banks.

According to Furfine (2003), there are two types of systemic risk: 1) the risk that a financial shock causes a set of markets or institutions to simultaneously fail to function efficiently; and 2) the risk that failure of one or a small number of institutions will be transmitted to others due to explicit financial linkages across institutions. To analyze contagion, Furfine estimates it by examining federal funds exposures across US banks, which are used to simulate the impact of exogenous failure scenarios. This paper concludes that, although the exposures are not large enough to cause a great risk of contagion, illiquidity could pose a threat to the banking system.

For Acharya (2009) systemic risk, defined as joint failure risk, arises from the correlation of banks' assets returns. To analyze this, the author considers a model in which banks invest in risky assets in various industries. The investment decision determines the correlation among banks' assets, which, in case it is high enough, results in a rising exposure to systemic risk. The paper concludes that the effect of regulation of banks' optimal investment decisions

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deserves careful scrutiny: requirements should depend both on banks' joint risk and on their individual risk.

On the other hand, Allen and Gale (2000) address systemic risk from a liquidity risk perspective. They find that the resilience of the interbank market to adverse liquidity shocks depends on the market's structure. Similarly, Saade Ospina (2010) analyzes the Colombian interbank collateralized market. He develops a centrality index using cooperative game theory and concludes that when the interbank network is disconnected, bid ask spreads are farther apart and their volatility is higher. This implies that banks are more exposed to liquidity market risk under this scenario.

Nonetheless, systemic risk has not been analyzed yet in Colombia from a market risk perspective. The exposure of Colombian financial institutions to this risk has increased since 2009 as lower rates and slower credit dynamics have caused asset restructuring. Treasury bond holdings and volatility in yields reached levels similar to those observed by mid 2006, when a setback in this market caused the most important losses during the past decade. In the context of the model proposed by Acharya (2009), this behavior has increased the correlation of the different entities' assets, especially among commercial banks, which could cause a higher systemic risk. Due to these reasons, it is imperative to analyze market risk dependence among Colombian commercial banks to identify which institutions have a high contribution to systemic risk.

The objective of this paper is to analyze market risk dependence among Colombian financial institutions in order to identify institutions with the highest contribution to systemic risk. We follow the definition of *CoVaR* introduced by Adrian and Brunnermeier (2009), which is measured as the Value at Risk (*VaR*) of a financial institution conditional on the *VaR* of another institution. In this way, if *CoVaR* increases relative to *VaR*, so does spillover risk among institutions. By defining the difference between these measures as *⊿CoVaR*, we can estimate the contribution of each institution to systemic risk.

Additionally, since *⊿CoVaR* is not necessarily symmetric (that is, the contribution that institution *i's VaR* has to institution *j's* market risk does not necessarily equal the contribution of *j's VaR* to *i's VaR*), this measure can be used to analyze the risk across the Colombian financial system. We focus on the public debt portfolio of financial entities and define the portfolio of the financial system as the aggregate public debt holdings of these institutions. Results suggest that risk codependence among entities increases during distress periods.

As mentioned by Adrian and Brunnermeier (2009), one advantage of *CoVaR* is that it can be applied with any other tail measure to analyze other risks. For instance, Chan-Lau (2008) follows a similar approach and assesses systemic credit risk by measuring default risk codependence among financial institutions through an analysis of CDS spreads of 25 financial institutions in Europe, Japan and the US.

Also, Gauthier et al (2010) compare *⊿CoVaR* and four other approaches to assign systemic capital requirements to individual banks based on each bank's contribution to systemic risk. The authors conclude that financial stability can be enhanced substantially by implementing a system perspective on bank regulation.

The remainder of this paper is structured as follows: section 1 describes the specification of the model used. In section 2 we analyze the Colombian Treasury Market. Section 3 shows the main results. Finally section 4 includes the concluding remarks.

1. Methodology

To study the systemic market risk contribution of each entity it is important to analyze the risk codependence among financial institutions in the context of a high market risk exposure scenario. Several methodologies have been used to measure systemic risk and risk codependence. Hartmann et al (2001) and Chan-Lau et al (2004), for instance, used extreme value theory for this purpose. However, a common problem of this methodology is that a large amount of data is needed because only tail observations are used.

An adequate way to measure market risk codependence is through quantile regression.[2] This methodology provides a more extensive analysis than ordinary least squares in the sense that it estimates the relationship among random variables under different quantiles. For this reason, it can be used to estimate the risk codependence among financial institutions under different risk scenarios. Additionally, this is a methodology that can be easily estimated with a large number of independent variables.

In general, the estimation of quantile regression consists in minimizing the sum of residuals, weighted asymmetrically by a function that depends on the quantile τ. That is, the τ regression quantile, $0 < \tau < 1$, can be represented as a solution of the following expression:

$$\min_{\beta} \sum_t \rho_\tau (y_t - f(x_t, \beta)) \qquad (1)$$

Where *y* is the dependent variable, $f(x_t, \beta)$ is a linear function of the parameters and the variables used to explain the behavior of *y*, and ρ_τ is the weight assigned to each observation, depending on the analyzed quantile τ. Specifically Koenker and Bassett (1978) propose the following representation of equation (1):

$$\min_{\beta} \left[\sum_{t \in \{t: y_t \geq f(x_t, \beta)\}} \tau |y_t - f(x_t, \beta)| + \sum_{t \in \{t: y_t < f(x_t, \beta)\}} (1 - \tau) |y_t - f(x_t, \beta)| \right] \qquad (2)$$

In this paper we measure how the risk level of a financial institution *j* is affected by the risk level of another financial institution *i* or by the whole financial sector. Following Chan-Lau (2008), equation (2) is estimated with:

$$y_t = Risk_{j,t} \qquad (3)$$

$$f(x_t, \beta) = \beta^{\tilde{R}}_{ji,\tau} \tilde{R} + \beta_{ji,\tau} Risk_{i,t},$$

Where $\mathrm{Risk}_{i,t}$ denotes an indicator that measures the market risk of entity *i* in *t*. For this purpose we use the daily *VaR* of entity *i's* TES portfolio, with a weekly frequency. $\beta_{ji,\tau}$ is a vector of parameters, which indicate risk codependence between *i* and *j* for quantile τ. These parameters were estimated for different quantiles in order to analyze if the risk codependence between any two entities or sectors increases under higher levels of risk.

In addition, we consider a matrix with exogenous variables that can affect the market risk level (R). R contains different aggregate risk factors that are used to explain the evolution of TES prices and its market risk, such as inflation expectations, weekly stock market returns and exchange rate returns, the slope of the yield curves, weekly credit growth, EMBI+ for Colombia, VIX, five-year CDS for Colombia and the Colombian interbank rate. To avoid multicollinearity, we estimated the principal components that explain 80% of the volatility of the standardized variables in R. The resulting vectors ($\tilde{R}$) were used in the quantile regressions. In this sense $\beta^{\tilde{R}}_{ji,\tau}$ can be understood as the effect of these exogenous variables over entity *j's* market risk on τ quantile, given *i's* market risk.

The estimation process required the calculation of 1360 regressions for banks: for each of the 16 Commercial Banks (CB) we calculated a regression against each other bank's *VaR*, and against an aggregate *VaR* for the banking sector, for five different quantiles. Similarly,

[2] This methodology was proposed by Koenker and Bassett (1978).

we estimated 210 regressions for Pension Funds (PF), due to the fact that we analyzed six PF and an aggregate *VaR* that comprised the market risk of the PF sector. Finally, we calculated an aggregate *VaR* for each consolidated sector of other Credit Institutions: Financial Corporations (FC), Financing Companies (CFC), and Financial Cooperatives (Coop). We did the same for each sector comprised in the other Non-Banking Financial Institutions (NBFI): Brokerage Firms (BF), Insurance Companies (Ins) and Hedge Funds (HF), and for the whole Financial System (FS). Then, we estimated 360 regressions among each sector of the financial system. The main results are shown in section 3.[3]

Additionally, to extend the systemic risk analysis, Adrian and Brunnermeier (2009) proposed a conditional risk codependence measure, or co-risk measure, which they denoted *CoVaR*.[4] $CoVaR_{\alpha}^{(j|i)}$ stands for the VaR_{α} of entity *j* conditional on the VaR_{α} of entity *i.* That is,

$$P\left(X^{i} \leq VaR_{\alpha}^{i}\right) = \alpha$$

$$P(X^{j} \leq CoVaR_{\alpha}^{(j|i)} \mid X^{i} = VaR_{\alpha}^{i}) = \alpha$$

Where X^{i} stands for weekly returns of the TES portfolio of entity *i*. A more general way to define $CoVaR_{\alpha}^{(j|i)}$ is:

$$CoVaR_{\alpha}^{(j|i)} = \left\{VaR_{\alpha}^{j} \middle| VaR_{\alpha}^{i}, R\right\}.$$

In this sense, equation (2), taking into account (3), represents the estimation of $CoVaR_{\alpha}$ by quantile regression. In order to calculate entity *i's* contribution to entity *j's* VaR_{α}, Adrian and Brunnermeier (2009) suggest the following expression:

$$\Delta CoVaR_{\alpha}^{(j|i)} = CoVaR_{\alpha}^{(j|i)} - VaR_{\alpha}^{j}, \qquad (4)$$

Where $\Delta \mathrm{CoVaR}_{\alpha}^{(j|i)}$ is the increase of *j's* market risk if entity *i's* market risk is considered. Taking into account (3), equation (4) can be expressed as:

$$\Delta CoVaR_{\alpha}^{(j|i)} = \beta_{j|i,\alpha}^{R} R + \beta_{j|i,\alpha} VaR_{\alpha}^{i} - VaR_{\alpha}^{j}.$$

The same analysis can be made between sectors and the financial system. In this sense, we can study the increase in the market risk of a sector or the whole financial system when the *VaR* of an entity is considered. This increase is the systemic market risk contribution.

2. TES Market and Data Analysis

Colombian Treasury Bond (TES) holdings account for over 20% of Colombian GDP: on March 2010 they reached approximately 120 trillion (t) Colombian Pesos (COP), or USD 60 billion (b), of which near to 45% were owned by the financial system. Figure 1 shows TES exposure by major entities in the Colombian financial system.[5] It can be seen that TES exposures of financial institutions have displayed an increasing trend since late 2008. Also, PF and CB have the highest share of these bonds in the financial system. In particular, by

3 Regressions were estimated with 360 weekly observations for the mentioned variables, with data from February 14th, 2003 to January 1st, 2010.

4 For a detailed explanation of the definition and properties of *CoVaR* see Adrian and Brunnermeier (2009).

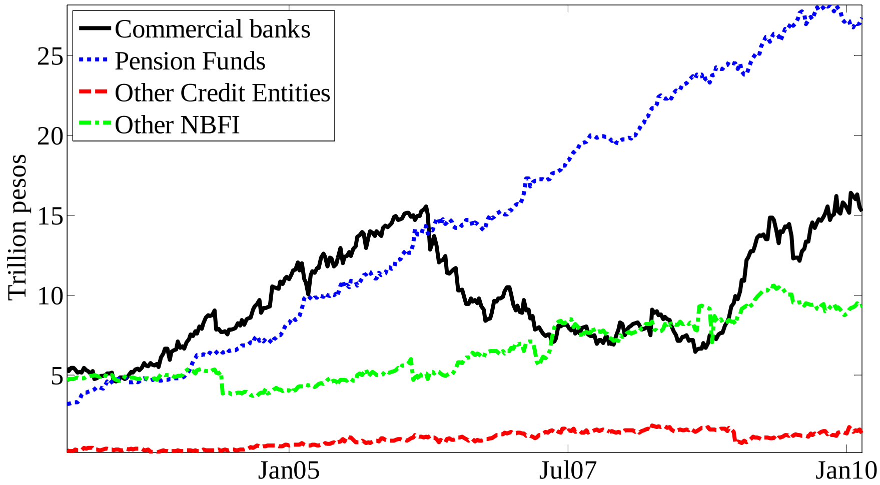
5 Credit institutions classify their investments as negotiable, available for sale, and those kept until maturity. Only the first two classes are subject to changes in market value. This corresponds to over 60% of total TES holdings. Figure 1 shows TES holdings in these classes.

December 2009 the TES exposure of both PF and CB was close to its historic maximum. By this date almost 33% of the above entities' investment portfolio was exposed to Colombian Treasury Bonds (COP 27.1 t).

With respect to CB, by late 2009 their TES exposure (COP 16.4 t) was over 10% of their loan portfolio. This amount was greater than the exposure of these entities to Colombian public debt by mid 2006, when a setback in the public debt market caused the most important losses during the past decade. This crisis was not only observed in the public debt market: the stock market was also affected, as the weekly returns of the Colombian Stock Market General Index (IGBC) show (Figure 7 in Appendix B, Panel B).[6]

Figure 1:

TES Exposure



Source: Banco de la República.

To study the TES exposure among the 16 CB and the six PF analyzed in this paper, a Herfindahl-Hirschman Index (HHI) was estimated (Figure 2). In this way, CB TES exposure can be considered as less concentrated than PF exposure, since the former's HHI is 887, on average, while the latter's is 2121. The difference in the HHI for CB and PF may be due to the number of analyzed entities of each type, and to the fact that there are two PF whose average TES exposure share of the total has been over 50%.

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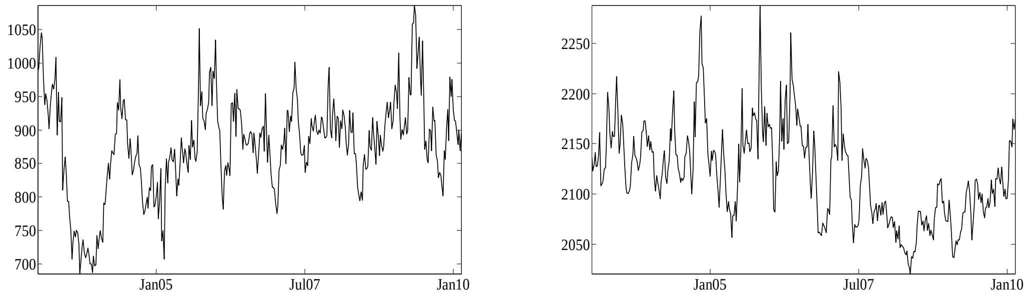
6 The intervention rate of the Banco de la República (BR) increased from 6% to 8.75% between May 2006 and one year later.

Figure 2:

Herfindahl-Hirschman Index for TES Exposure

A. Commercial Banks **B. Pension Funds**



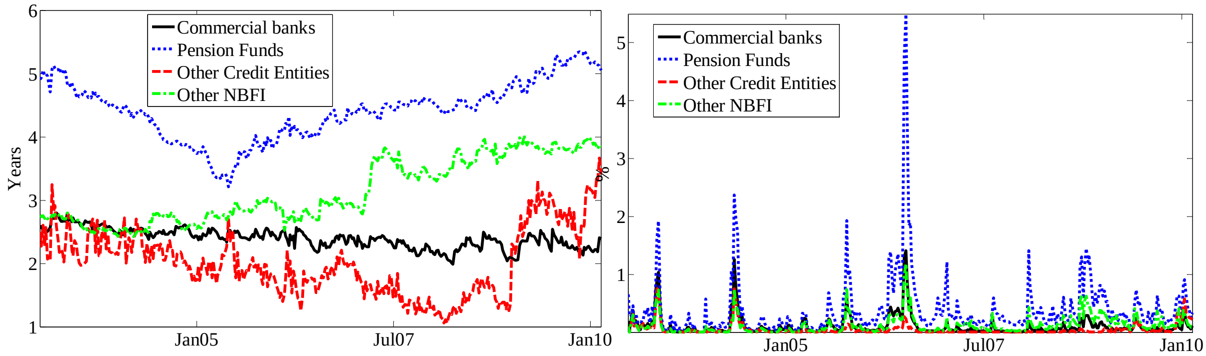
Source: Banco de la República.

It is important to mention that CB have portfolios with lower duration than PF, due to their different liability maturity. While the CB TES portfolio has consistently had a duration of around 2.5 years, the TES portfolio duration of PF reached 5.0 years in February 2010. On the other hand, the duration of the TES portfolio of other Credit Entities and other NBFI reached 3.4 and 3.8 in February 2010, respectively (Figure 3, Panel A). Although a higher duration indicates a more elevated interest rate risk, this difference among portfolio compositions across the term structure does not necessarily imply different exposures to market risk shocks. For this reason, we also analyze the *VaR* of the portfolios.

Figure 3:

TES Portfolios

A. Duration **B. 99% *VaR***



Source: Banco de la República.

Figure 3, Panel B, shows the daily 99% *VaR* for the TES portfolio for each type of financial entity.[7] It can be seen how the TES crisis of 2006 was reflected in a relatively high *VaR* for every type. Nonetheless, the exposure of the PF TES portfolio to market risk was especially high. Moreover, although the recent international financial crisis also affected financial entities, their portfolios were not as exposed to market risk as during 2006.

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7 *VaR* was estimated following the methodology explained in Martínez and Uribe (2008).

VaR estimations were used to calculate the *CoVaR* of different financial entities, as is explained in section 1. Additionally, in order to incorporate idiosyncratic risk into the analysis, other variables were used in the estimation (matrix $\bar{R}$ in (3)).[8]

3. Results

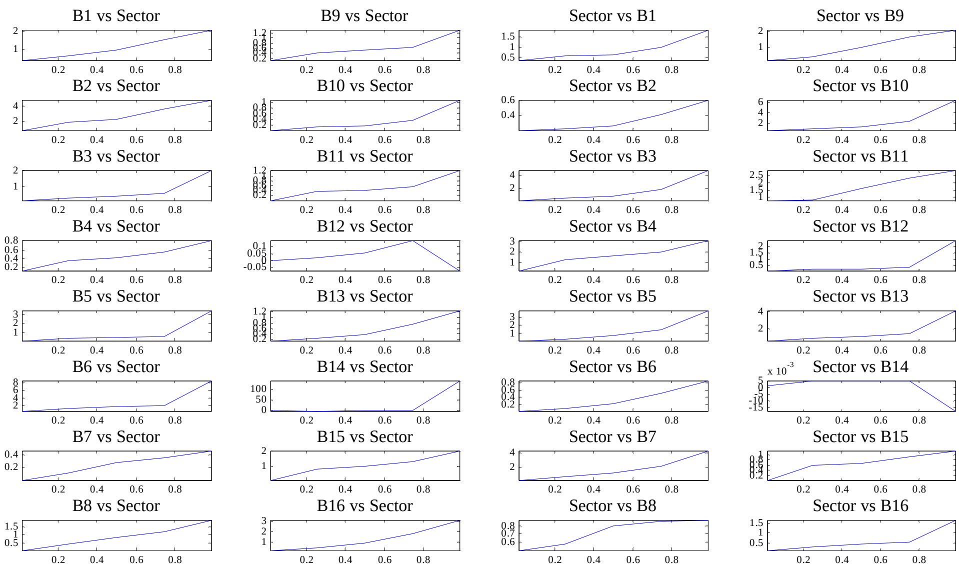
Risk codependence relations were estimated using quantile regressions for commercial banks, pension funds and different sectors within the Colombian financial industry. This approach is useful to estimate the systemic relations for processes determined by important changes in their volatility through time.[9]

In addition, high quantiles correspond to exercises where observations located in the right tail of the distribution are used to determine the risk codependence according to equation (3). Therefore, extreme observations materialized only in particular periods of time that can be considered as periods of crisis, are highly weighted in the estimation of this model. On the other hand, low quantiles represent the average state of an economy, due to the fact that the model weights in a similar way observations above and below the quantile.

High risk codependence between entities can be observed through $\beta_{j|i,\tau}$ defined in equation (3). Figure 4 presents the evolution of this parameter for CB across different quantiles and regressions estimated between each bank and the whole banking sector. Each graph corresponds to the particular $\beta_{j|i,\tau}$ obtained in each of the regressions evaluated on five different quantiles.

Figure 4:

Risk Codependence Among Commercial Banks



Source: Authors' estimations.

8 Appendix B shows the different variables used and their dynamics since 2003. The variables used are inflation expectations, weekly stock market returns and exchange rate returns, the slope of the yield curves, weekly credit growth, EMBI+ for Colombia, VIX, five-year CDS for Colombia and the Colombian interbank rate.

9 Quantile regressions were estimated using $\tau \in \{0.01, 0.25, 0.5, 0.75, 0.99\}$.

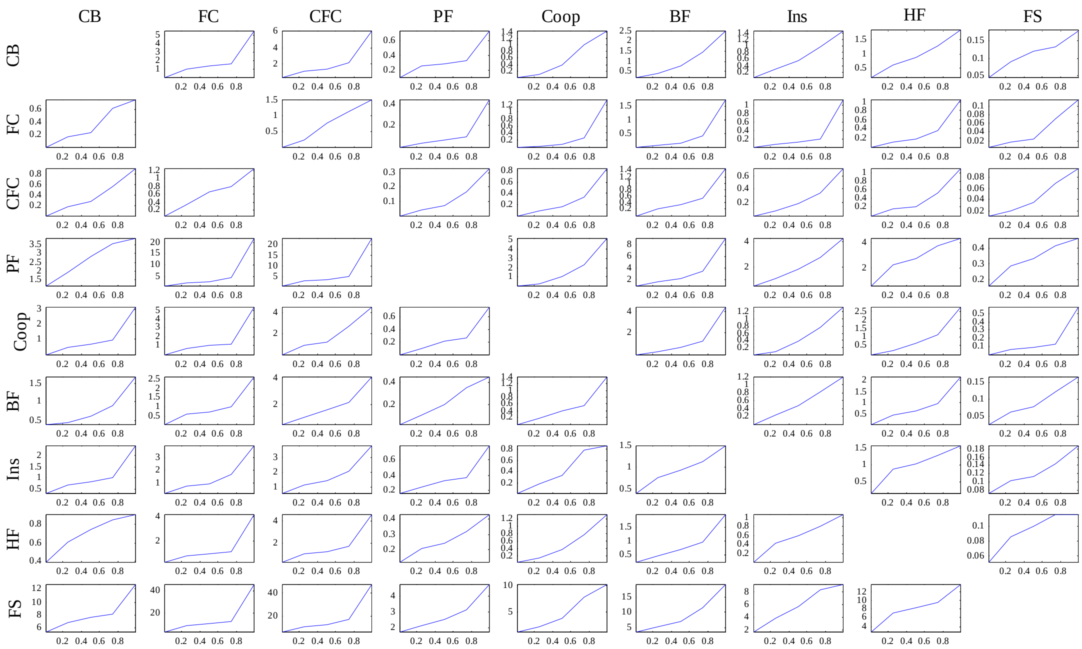
From these results, it can be claimed that $\beta_{j|i,\tau}$ increases as τ increases as well. This suggests that the correlation between different agents' market risk becomes larger during distress periods which are represented by higher quantiles. In addition, it is important to notice that this behavior is observed in both directions: the contribution of each bank to the system's market risk increases in stress periods as does the effect of systemic market risk on each entity's particular risk during the same events.

Nonetheless, agents' contributions to systemic market risk are different in size. In particular, banks 7, 10 and 13 show the most significant contribution to systemic market risk per *VaR* unit, taking into account the magnitude of each $\beta_{j|i,\tau}$.

These increasing tendencies for $\beta_{j|i,\tau}$ are also observed among pension funds (Figure 6 in Appendix A) where $\beta_{j|i,\tau}$ expands as higher quantiles are considered in the regressions. In addition, this is the same behavior that can be observed in the analysis of the financial sector. In Figure 5 each graph corresponds to the quantile regressions estimated for the market risk of the row-sector as a function of the macroeconomic variables and the *VaR* of the column-sector.

Figure 5:

Risk Codependence Among Financial Sectors



Source: Authors' estimations.

Although the size of $\beta_{j|i,\tau}$ can suggest the magnitude of the contribution of each entity to the systemic market risk, $\Delta CoVaR_{\alpha}^{j|i}$ represents a more robust method to estimate this measure, due to the fact that $\Delta CoVaR_{\alpha}^{j|i}$ estimates the exact contribution of each entity to systemic market risk. Table 1 presents the results obtained for this indicator on CB for τ = 0.99. Values included in the left column correspond to the system's contribution to the market risk of each individual bank, while the right represents the opposite relation: the contribution of each bank to systemic market risk. In this sense, the former permits us to identify the most vulnerable entities to systemic market risk while the latter presents the entities that contribute the most to the system's risk.

According to these results, it can be claimed that commercial banks display heterogeneous behavior regarding their contribution to systemic market risk. While there are several banks which are not significantly affected by the sector's market risk (for instance, banks 4, 7, 9, 10, 11, 13 and 14), there are others which are more affected by it (banks 6, 12 and 16). Moreover, only two entities have an important contribution to the system's market risk that can be considered significantly elevated. It is important to notice that the most vulnerable entities are not those which present the highest contribution to the sector's systemic market risk. Table 4 in Appendix A shows similar results for PF.

Table 1:

Conditional Risk Codependence Among Commercial Banks

	CB vs Sector	Sector vs CB
CB1	0.14%	0.05%
CB2	0.16%	0.02%
CB3	0.09%	0.28%
CB4	0.02%	0.08%
CB5	0.07%	0.18%
CB6	0.95%	0.13%
CB7	0.03%	0.28%
CB8	0.07%	0.25%
CB9	0.03%	0.34%
CB10	0.02%	0.39%
CB11	0.03%	0.03%
CB12	0.27%	1.68%
CB13	0.04%	0.14%
CB14	0.00%	2.48%
CB15	0.18%	0.11%
CB16	0.28%	0.79%

Source: Authors' estimations.

According to the $\Delta CoVaR_{0.99}^{(A)}$ estimated for the financial system (Table 2), it can be inferred that FC, Coop and HF are the sectors that contribute the most to systemic market risk. Nonetheless, Table 2 presents the codependence results observed during the last week of 2009, which is a period when these entities registered a higher increase in *VaR* than the rest of the sectors. It can also be claimed that Coop are the most vulnerable entities to the systemic market risk and, in general, to the market risk of the other sectors.

Table 2:

Conditional Risk Codependence Among Financial Sectors

	CB	FC	CFC	PF	Coop	BF	Ins	HF	FS
CB	0.00%	1.35%	0.33%	0.17%	0.51%	0.01%	0.09%	0.29%	0.10%
FC	0.13%	0.00%	0.13%	0.12%	0.12%	0.13%	0.16%	0.12%	0.11%
CFC	0.02%	0.33%	0.00%	0.09%	0.08%	0.01%	0.08%	0.13%	0.06%
PF	0.14%	5.07%	0.31%	0.00%	1.14%	0.12%	0.52%	1.10%	0.11%
Coop	0.88%	2.51%	1.11%	1.51%	0.00%	1.16%	1.20%	1.05%	0.50%
BF	0.00%	0.92%	0.04%	0.06%	0.59%	0.00%	0.25%	0.45%	0.10%
Ins	0.54%	1.24%	0.60%	0.39%	0.56%	0.66%	0.00%	0.59%	0.44%
HF	0.00%	1.00%	0.03%	0.01%	0.15%	0.01%	0.04%	0.00%	0.01%
FS	0.85%	13.08%	1.31%	1.97%	3.85%	1.06%	1.62%	2.19%	0.00%

Source: Authors' estimations.

We estimated the historical average conditional risk codependence of the financial system with the purpose of reducing the effect of high changes of *VaR* on $\Delta CoVaR_{\alpha}^{(A)}$. This average allows us to identify which are the most vulnerable and systemic entities in terms of market risk, across the sample. Table 3 presents these results, which also suggest that FC and Coop are the sectors with the highest contribution to the system's market risk. Nonetheless, this contribution is not as high as that observed in Table 2.

Table 3:

Historical Conditional Risk Codependence Among Financial Sectors

	BAN	CF	CFC	PF	COOP	COM	INS	FID	FS
BAN	0.00%	0.24%	0.29%	0.16%	0.30%	0.16%	0.19%	0.13%	0.07%
CF	0.15%	0.00%	0.15%	0.17%	0.22%	0.22%	0.20%	0.14%	0.14%
CFC	0.10%	0.16%	0.00%	0.11%	0.14%	0.11%	0.12%	0.11%	0.07%
PF	0.35%	1.07%	0.98%	0.00%	1.15%	0.87%	0.53%	0.42%	0.20%
COOP	0.68%	0.80%	0.54%	0.73%	0.00%	0.64%	0.62%	0.63%	0.46%
COM	0.20%	0.43%	0.21%	0.17%	0.33%	0.00%	0.18%	0.24%	0.13%
INS	0.38%	0.38%	0.37%	0.29%	0.40%	0.39%	0.00%	0.32%	0.24%
FID	0.15%	0.28%	0.26%	0.17%	0.28%	0.21%	0.21%	0.00%	0.14%
FS	1.31%	2.90%	1.80%	1.24%	2.49%	1.69%	1.11%	1.10%	0.00%

Source: Authors' estimations.

This particular behavior presented by FC and Coop can be explained by the dynamic portfolio composition of these entities. They are financial institutions which permanently modify the composition and the size of their investments in TES. Therefore, they present a high volatility in their portfolios' returns compared to other sectors with bigger and more stable portfolios. In consequence, results suggest that sectors with high levels of volatility generate more systemic market risk than entities with bigger positions in these investments. In this way, institutions with a higher share in the TES market could have a higher systemic market risk contribution if their portfolio becomes more dynamic.

4. Concluding Remarks

In Colombia market risk increased significantly during 2009. However, this risk has not yet been analyzed from a systemic perspective. The objective of this paper was to analyze market risk codependence among Colombian financial institutions using *CoVaR* estimations. For this, quantile regressions were calculated, and Δ *CoVaR* was used as a measure of systemic market risk contribution.

Results suggest that risk codependence increases during distress periods. This is a general result that can be observed among commercial banks, pension funds, and between different types of financial institutions. In this way, entities which have a higher contribution to systemic market risk should be carefully monitored to avoid negative externalities caused by larger correlations. Also, regulation should consider the systemic contribution when designing risk requirements to minimize the adverse consequences of possible herding behavior.

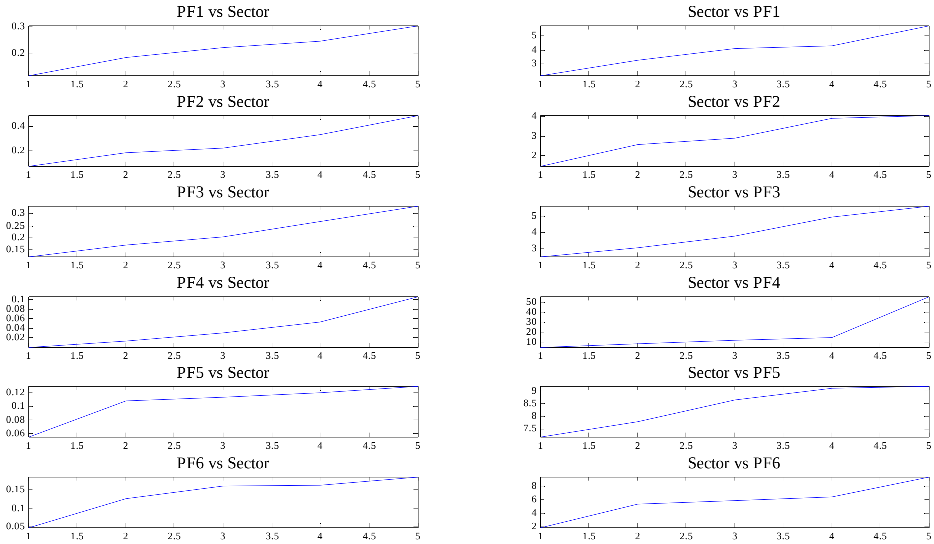
According to Δ *CoVaR* estimations, FC and Coop are the sectors that have the highest contribution to systemic market risk. Nonetheless, it is important to mention that there are some caveats that should be considered. This measurement is highly sensitive to current changes in *VaR* estimations. Therefore, entities with higher changes in their portfolio returns appear to be more systemic than those with more stable returns and bigger positions in these investments. Additionally, since the analysis is based on quantile regressions, Δ *CoVaR* does not explain the specific channel by which the risk of one entity affects another entity's risk measurement. In this way, Δ *CoVaR* can only be interpreted as a codependence measurement. Improvements in the estimations to overcome these and other shortcomings are left for future analysis.

Appendices

A Additional Results

Figure 6:

Risk Codependence Among Pension Funds



Source: Authors' estimations.

Table 4:

Conditional Risk Codependence Among Pension Funds

	PF vs Sector	Sector vs PF
PF1	0.05%	0.55%
PF2	0.78%	0.20%
PF3	0.29%	0.02%
PF4	0.16%	2.79%
PF5	0.12%	0.01%
PF6	0.63%	0.75%

Source: Authors' estimations.

B Dynamics of Variables Used for PCA Estimation

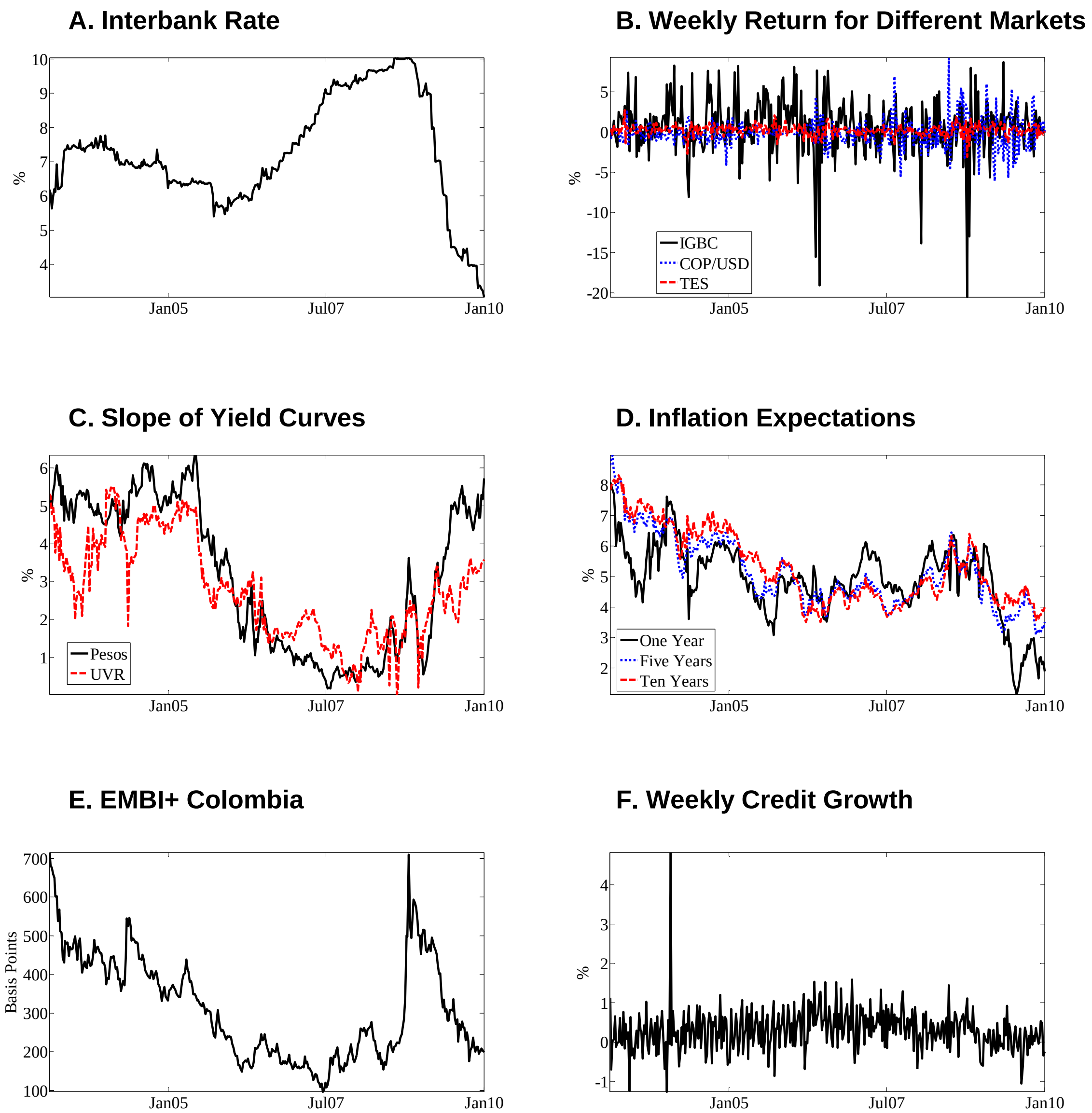
Figure 7, Panel A, shows the interbank rate, which follows closely the intervention rate of BR. In May 2006 BR began a monetary contraction by raising its intervention rate from 6% to 10% during a time span close to two years. Due to the financial crisis, this rate was lowered from 10% to 3.5% in less than one year, beginning in December 2008. This behavior had a positive effect on the public debt market, as the TES index return shows in Figure 7, Panel B. This figure also shows that the TES crisis in 2006 and the recent international financial crisis had a significant negative effect on the Colombian stock market.

By comparing panels A and C of Figure 7 it can be concluded that periods of monetary expansion match with periods of steep yield curves. This is observed both in the COP-denominated TES yield curve and in the inflation-linked TES (UVR) yield curve. On the other hand, periods with an increasing intervention rate have occurred at the same time that yield curves have flattened. Additionally, by analyzing the difference between these two yield curves, inflation expectations can be estimated. Panel D of Figure 7 shows that they have a decreasing trend in the analyzed period.

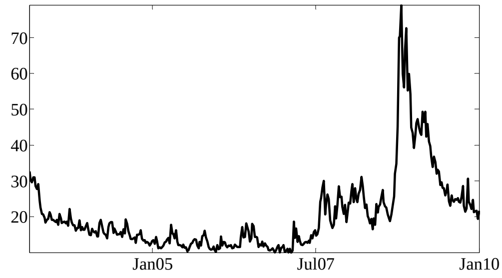
Panel F of Figure 7 shows the weekly growth of the credit stock. On average, credit has increased 0.3% each week. However, it has had a relatively high standard deviation of 0.5%. In particular, in the last week of January 2004 credit grew over 4% with respect to the previous week. During 2009, however, the average weekly credit growth was 0.03%, showing the slower dynamics the credit stock had due to the economic turndown of Colombia during that year. Finally, panels E, G and H of Figure 7 show the EMBI+ for Colombia, VIX and five-year CDS for Colombia, respectively. The dynamics of these indexes have been closely related since the beginning of the recent financial international crisis. In particular, the bankruptcy of Lehman Brothers was reflected in a historic increase in the three indexes.

Figure 7:

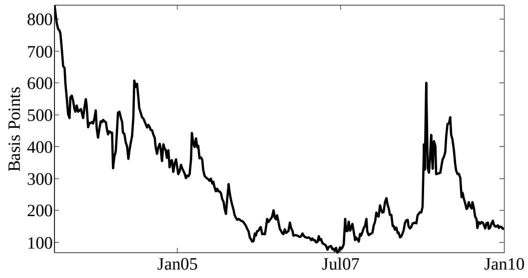
Variables Used for PCA Estimation



G. VIX



H. Colombia five-year CDS



Source: Banco de la República, Bolsa de Valores de Colombia (Colombian Stock Market), Reveiz and León Rincón (2008), Bloomberg.

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