ANALYZING THE SIZE, DIFFUSION, AND SPILLOVER OF LOANS RISK

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Abstract

We analyze the diffusion and spillover effects of credit risk among banks within a banking system, using the Mexican financial system as case study. Our proxy to measure credit risk is the non-performing loans ratio (NPL). For this purpose we construct a VAR model to identify the composition of the variance of NPL's ratios dividing it into two parts: one that is explained by the VAR coefficients, and the other attributed to the contemporary "error" or "shocks" on other banks in the system. The error in the structural model represents the "news" that disturbs the stable risk in each period. Our work builds on the spillover index proposed by Diebold and Yilmaz (2009) that indicates the degree on which the overall risk in the system is explained by the spillover effects. The method allows us to measure the long-run contributions of each bank's risk on the rest of the banking system through the diffusion of risk between intermediaries. Moreover, we are able to gauge the relative importance of spillover by increasing the length of prediction periods for each bank's NPL. Our estimations for the Mexican banking system between 2002 and 2013 suggest that the overall spillover effect index accounts for 15 percent of the aggregate risk's observed variation in the short term and almost 40 percent in the long term. The spillover effect explains 32 percent of total risk in the short term and 78 percent in the long term when we control for individual bank's characteristics, even though the total size of risk originated by news in the banks decreases relative to the model without control variables.

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Resumen

En este trabajo analizamos los efectos de difusión y de derrama (spillover) del riesgo crediticio entre bancos dentro de un sistema bancario, utilizando el sistema financiero mexicano como caso de estudio. Nuestra selección de medida de riesgo crediticio es la razón de crédito en situación de mora como porcentaje del total de crédito en cada banco (NPL). Para este propósito construimos un modelo VAR que identifica la composición de la varianza en las razones de NPL, y lo dividimos en dos partes: una explicada por los coeficientes del modelo VAR, y otra explicada por el "error contemporáneo" o las "innovaciones" de cada banco en el sistema. El error en el modelo estructural representa las "noticias" que distorsionan el nivel de riesgo estable cada período. Nuestra investigación se basa en el índice de derrama (spillover index) propuesto por Diebold y Yilmaz (2009) el cual indica el grado sobre el cual el riesgo agregado de un sistema es explicado por estos efectos de derrama. Este método nos permite cuantificar las contribuciones de largo plazo del riesgo de cada banco sobre el resto del sistema bancario, a través de la difusión del riesgo entre intermediarios. Además de lo anterior, el método nos permite identificar la importancia relativa del efecto de derrama incrementando gradualmente el período de predicciones para cada razón de NPL de cada banco. Nuestras estimaciones para el sistema bancario mexicano entre 2002 y 2013 sugieren que para el total de la variación en el riesgo del sistema el índice de derrama representa 15 por ciento de la variación en el corto plazo y casi 40 por ciento de la variación en el largo plazo. Por otra parte, cuando se controla por las características individuales de los bancos, el efecto de derrama representa 32 por ciento del riesgo total en el corto plazo, y 78 por ciento del riesgo en el largo plazo, sin embargo el tamaño del riesgo total originado por las noticias de los bancos (innovaciones) decrece.

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1. Introduction

The non-performing loan (NPL) ratio is one of the key indicators in assessing the quality, riskiness and solvency of banks. This variable indicates the degree of deterioration of the credit portfolio for individual institutions or an entire banking system. Specifically, it represents the percentage of loans that have not been collected according to the previously agreed upon terms and conditions. These loans will most likely never be fully recovered. The relevance of this ratio is straightforward: when debtors stop paying, the bank's liquidity and profitability progressively decreases. A bank approaches to an unsafe limit when it is unable to pay interest expenses, to cover operating costs or, in extreme circumstances, to repay depositors.

Factors affecting the NPL ratio have been a topic of interest for researchers. For instance, a large body of literature has proved that the macroeconomic environment or banking sector factors have explanatory power at the level of the NPL ratio.[1] Variables such as GDP, exchange rates, foreign currency assets, purchase power parity, bank capitalization, financial deepening, loan-to-assets ratio or deposits to loans significantly explain the variation of the NPL ratio. In this study, we take a new point of view and we model the NPL ratio by analyzing

[1] See, for instance, Festic, Kavkler and Repina (2011) for a summary of such studies and their main findings.

the degree of spillover, or contagion, over time between the NPL ratios from several banks within a single banking system. In particular, knowing that each institution implements its own credit policies and has its own risk appetite, we explore the interaction between NPL ratios of the different institutions.

In this paper we use NPL ratios as a proxy measure of credit risk to determine the size, the degree of influence and the diffusion process of other banks' credit risk on the rest of the banking system. For this purpose we use forecast errors decomposition obtained from a vector autoregressive (VAR) specification, obtaining the variance of the errors for different time horizons. The errors represent the importance of "new" or innovations on NPL ratios, or credit risk, besides long run trends and persistence. First, we use the determinant of variance-covariance matrix of errors for each of the forecast k-steps ahead as a measure of the size of the contributions to credit risk due to the innovations in news from each bank. We define the aggregate contribution of news to credit risk of the system in terms of log-values of the variance-covariance matrix to compare the size of risk among different specifications and over time. Second, using the variance of the errors decomposition, we apply the spillover index method proposed by Diebold and Yilmaz (2009) that defined the index as the percentage of forecast error variance from one entity that can be attributed to other entities. They used this method to assess the degree of interaction between returns and the volatility of different equity markets around the world, providing an intuitive measure for this interdependence. The main advantage of the spillover method is that it reports a measure of contagion within the system derived from the exogenous innovations on risk. We adapt their method to identify the long-run equilibrium of credit risk interdependence between banking institutions and to determine how the risk of contagion takes relevance as we increase the timeframe of prediction. That is, we explain how this external influence on credit risk in terms of innovations evolves and spread over time; namely, the persistence of risk transmission of the banks in the system. We recognize that banks operating within one economy suffer from both internal and common shocks. However, we assert that at some point in time those common shocks overcome individual risk factors becoming the main drivers of credit risk. In other words, this approach allows us to establish when individual policies and own internal risk stops being relatively relevant and when the changes of individual banks credit risk are mainly the result of the contagion of widespread innovations.

To perform our study, we use data on total assets, total loans, interbank loans, and NPL ratios for the whole credit portfolio and for three types of credit-commercial, consumer and mortgages-from 18 Mexican banks between 2002 and 2013. The banks in the sample consistently represent around 90 percent of the total assets of the system and 96 percent of total loans. According to our results, the spillover effect between banks in the long run accounts for approximately 40 percent of a bank's NPL ratio variance over a forecast period of 3 years. If we control for the size of the bank, the credit growth rate and the activity in the interbank market, the spillover effect is almost 80 percent. This finding indicates that changes on NPL ratios in the long run are mostly attributed to common risk factors and that only 20 percent is the result of intrinsic risk factors in each bank. The progressive increase of the forecast window (from 1 to 36 months) shows that the diffusion process is increasing up to certain long-run equilibrium level. Considering a one-month forecast horizon, there is a low degree of spillover-around 15 percent-rapidly increasing to 33 percent in three months, and reaching the long-run equilibrium in approximately 12 months. In other words, intrinsic factors progressively become less relevant and other institutions credit risk take place explaining each other risk. In sum, the spillover effect explains a larger percentage of the aggregate risk as we increase the forecast period. Our estimations also show that not only the spillover effect increases over time but also the size of the risk common to all entities. Furthermore, the same pattern appears when we include exogenous variables in the VAR specification, although the size of the risk decreases. Regarding the type of loan, the highest spillover effect is for consumer loans and the lowest for mortgages, which could imply that loans with physical guaranties tend to be less expose to systemic risk. All results are quantitatively robust to the reordering of input variables, as VAR estimations are sensible to the input order of the entities. In this sense, our purpose is not to assess the causality of risk diffusion between banks but rather to measure the level of spillover in the whole system.

We contribute to the literature in several ways. First, we apply a method created to determine interdependence between stock exchanges to answer a question about credit risk spillovers within a banking system. Second, although we do not specifically define which are the common elements modifying credit risk in the system, we assess the relevance and the evolution of those exogenous elements on individual banks' risk. Third, we add to the original method by extracting more information from the VAR specification, namely, the determinant of the errors variance-covariance matrix to measure the size of the risk in the system. Additionally, by using not just one forecast period, but progressively increasing the length of the prediction horizon, we are able to study the persistence and the diffusion process of credit risk on each entity over time. As the forecast horizon is expanded, it becomes possible to describe how the NPL diffusion process takes place and how the risk arising from common shocks becomes relevant over time as measured by the spillover index.

The rest of the article is organized as follows. The second section briefly reviews some related studies. The third section presents the relevant methodology. The fourth section describes the data and provides a short overview of the Mexican banking system and the credit business over the studied period (2002-2013). The fifth section shows the estimations and results, and we conclude in section six.

2. Related Studies

Literature on banking, financial distress, and contagion has used the NPL ratio in very different ways. Up to and including the 1990s, this variable was used for models that assessed asset quality (Meeker and Gray, 1987), banking failures (Barr, Seiford, and Siems, 1994), financial crises and interest rates spreads (Rojas-Suarez and Brock, 2000), or bank costs and economies of scale (Bernstein, 1996). Most literature in banking failures has demonstrated that large proportions of non-performing loans are a significant predictor of future insolvency.

Non-performing loans appeared as dependent variable in few cases, and usually, in combination with other variables, it was part of the definition of a dummy variable which indicated the failure of a bank or defined a situation of financial crisis. For example, it was included in indexes measuring distress such as in Demirguc-Kunt and Detragiache (1998). Gonzalez-Hermosillo (1999) in particular recognized a high level of non-performing loans in a bank as a signal of seriously flawed prior practices, for example, high levels of risk taking and poor lending practices.

Studies using NPLs as a dependent variable appeared in the literature in late 1990s. For example, a widely cited study is Berger and DeYoung (1997), which related cost efficiency to troubled loans, finding that low levels of cost efficiency Granger-cause increases in non-performing loans. Their premise is that cost-inefficient managers are also poor loan managers. Espinoza and Prasad (2010) use a sample of banks in the Gulf Cooperative Council and the logit transformation of the NPL ratio as dependent variable. Their results show that both macro factors and bank-specific characteristics influence the level of NPLs. Particularly, they show that non-oil GDP, the VIX index proxy for global risk aversion, interest rates, and banking factors such as the size of capital, credit growth, and efficiency are all relevant. Festic, Kavkler and Repina (2011) model non-performing loans for new European Union members (Estonia, Latvia, Lithuania, Bulgaria and Romania) using cointegration analysis, correlations, cross-country regressions and panel regressions. According to their findings, the NPL ratio worsens with foreign direct investment in financial intermediation, the increase in real estate market, increases in the deposit to loan ratio, excessive credit lending and the amount of available banking finance. On the other hand, the loan to asset ratio, increasing economic activity, the growth of compensation of employees to the demand of household ratio and compliance with Basel core principles all have a positive influence on the NPL ratio. Finally, Tabak, Fazio and Cajueiro (2011) explore the relation between loan portfolio concentration and a banks risk and return in Brazil. Using the logarithm of a bank's NPLs as proxy for risk, they show that loan portfolio concentration increases returns and reduces default risk, and that the impact of concentration on a bank's return decreases with the bank's risk.

The second relevant body of literature for our study is focused on identifying and measuring the contagion and risk across banks in a system or across countries. It is worth noticing that the definition of contagion is very broad and that it depends on the context and studies. For this reason, we prefer to use the term "diffusion" to describe how an innovation in one institution influences each element within the system.[2] For example, Eichengreen, Rose and Wyplosz (1996) define contagion as the increase in the probability of a domestic crisis when a crisis somewhere else occurs, even when fundamental factors have been considered. Kaminsky and Reinhard (2000) use that definition as well to analyze transmission channels globally and regionally by using 80 currency crisis episodes from 20 countries in Europe, Asia and Latin America. They assert that the probability of contagion is higher at regional levels than at the global level because the ability to predict a domestic crisis, given a crisis somewhere else, depends highly on location. Their main finding is

[2] For detailed explanation about definitions of contagion, see Goldstein, Kaminsky and Reinhart (2000), and Reinhart and Rogoff (2009).

that some of the contagion attributed to trade can be related to linkages in the financial sector, principally common bank lenders. In this line, contagion has proven to be relevant in assessing bank fragility even with other approaches. Gonzalez-Hermosillo, Pazarbaşioğlu and Billings (1997) conclude that the contagion effects in Mexico, defined by interbank activities, might play a role in both the likelihood and timing of failure, as they tend to rapidly increase before crisis periods. They found that a higher percentage of NPLs in a portfolio increases the fragility of the banks in a system after some threshold level, while the macro exposure of the system is determined by the banks' growth in lending.

Furfine (2003) classifies two types of methods for identifying the contagion risk across banks. The first set of studies uses some external macro event to measure the spreading of risk within a system. The second type uses transactions across banks to quantify the extent of the risk transmission. With the second method, he analyzes the interbank relative exposures in the US banking system in February-March 1998, quantifying the potential contagion effect from one bank to the other. Furfine showed that the total losses in the economy due to contagion are small and approximately one percent of the assets in the system.

In a more recent paper, Dungey, Fry, González-Hermosillo and Martin (2005) present a large review of empirical models of contagion in the context of country-spread risk in the Asian economies. Their main findings are that the models explored are largely determined by the properties of the dataset employed and that further analysis needs to be undertaken in the form of Monte Carlo experiments to analyze the statistical properties of each model presented.

3. Methodology

Our study aims to measure three different aspects of risk within a banking system, namely the size of risk of the system, the importance of the relative contribution of other banks risk over each peer member for a given period, and the persistence of spillover transmission in time of risk among members within a system. For this purpose, we construct a VAR model to identify the composition of the variance of NPL's ratios dividing it in two parts. First, the one explained by the VAR coefficients associated to the model estimation in terms of the NPL ratio persistence and the exogenous variables. The second one is the portion explained by the contemporary "innovations" on each bank representing the "news" over the stable risk level in each lag considered in the model. In this line, our definition of "long run" or equilibrium of the systemic risk in the banking system is the VAR model of NPL ratios of banks. This model defines the vector of contributions of each entity to the long run risk of others banks (effects on the stable mean). On the other hand, the VAR errors represent the innovations or the "short run" idiosyncratic risks faced by banks given news in each period. These innovations contribute to risk both in the short run and in the long run, within and across banks in a system.

Given the VAR model, the size, diffusion and persistence of risk measures are built on the spillover index idea of Diebold and Yilmaz (2009), which is based on error in forecast variance decomposition. The variance decomposition allows us to identify the size and diffusion of risk among economic agents, banks in our case, in a closed system. Moreover, the spillover index permits to measure the overall contribution of the diffusion among the members of the system and to analyze such variables under different regimes and scenarios.

As in Berger and DeYoung (1997), we assume that for a given period t the long-run aggregate credit risk of the banking system is represented in terms of the individual NPL ratios of the banks in the economy. Therefore the time series data of NPL ratios of each bank enter the model as the variable of interest. In particular, we consider that the long-run aggregate bank risk ε_t relates to the profile of a contemporary individual bank's risk X_t, following a vector autoregressive (VAR) equilibrium representation in terms of history of news. Specifically, the infinite moving average representation of the vector of news is:

$$\mathbf{X}_t = \mathbf{\Phi}(L)\varepsilon_t \tag{1}$$

where L refers to the number of lags considered in the moving average representation of the risk diffusion process. Following the traditional VAR literature, the aggregate risk ε_t in the model shows the history of "shocks", "innovations" or "news" of the process. Therefore, the contemporary risk $\mathbf{X}_t$ is represented as a relative cumulative weighted sum of news across time, and among members of the system. The $\mathbf{\Phi}(L)$ vector is obtained using the ML-VAR estimation. With this set of parameters, we rewrite the model in terms of the normalized moving average as:

$$\mathbf{X}_t = \mathbf{A}(L)\mathbf{u}_t \tag{2}$$

where $\mathbf{A}(L) = \mathbf{\Phi}(L)Q_t^{-1}$,$\mathbf{u_t} = Q_t\varepsilon_t$ $E(\mathbf{u_t}\mathbf{u'_t}) = I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t.

From equation (2) we can construct the Wiener-Kolmogorov linear least-square forecast of the future risk for each bank using date "t" for information future period "$t+k$", where "k" refers to the number of forward periods in the estimation of the risk using the estimated coefficients $\hat{\mathbf{A}}(L)$. The vector forecast of the individual risk is ${}_t\hat{\mathbf{X}}_{t+k}$ using information up to "t" in terms of the following equation:

$${}_t\hat{\mathbf{X}}_{t+k} = [\hat{\mathbf{A}}(L)]^{\mathrm{k}}\mathbf{X}_t \tag{3}$$

Using the forecast estimation of the individual risk profile for a future period "k", the corresponding "prediction error", in terms of a within subsample of the data, is calculated as:

$$\mathbf{e}_{(t+k)} = \mathbf{X}_{(t+k)} - {}_t\hat{\mathbf{X}}_{(t+k)} \tag{4}$$

Following our line of thought, this error represents the importance of "news" in the corresponding forward period with respect to the long run model equilibrium. The estimated innovation allows us to measure the absolute and relative contribution of risk on each bank and across banks, once we calculate the sum of all forecasting errors.

With the error in forecasting for each bank in the system, it is possible to identify the covariance matrix of this vector of elements defined by:

$$\Omega_{\mathrm{t+k}} = E[\mathbf{e}_{t+k}\mathbf{e}_{t+k'}] \tag{5}$$

The Ω_{t+k} matrix in (5) defines the interaction between NPL risk and news in "$t+k$" which by definition is positive semi-definite. Therefore, the size of the risk in the system can be approached through the determinant of the matrix: $\det[\Omega_{\mathrm{t+k}}]$. If the determinant is zero, it would imply that the risk of the system is highly collinear and entirely determined inside the system persistence and not through the news. On the other hand, if the determinant is relatively high would suggest that the risk is not collinear among banks and that the system has a more disperse risk diffusion. As a result, for our purpose, the size of the system risk is approximated by $\det[\Omega_{\mathrm{t+k}}]$: the higher the value of the determinant, the larger the size of the risk attributed to news of each bank at that stage of the forecasting.

Following equation (5), we use the covariance Ω_{t+k} to identify the corresponding Cholesky decomposition matrices. In particular, we know that there exists an implicit normalized matrix $\hat{\mathbf{A}}(\mathrm{L})_{t+k}$ such that:

$$\mathbf{e}_{t+k} = \mathbf{X}_{t+k} - {}_{t}\mathbf{X}_{t+k} = \hat{\mathbf{A}}(\mathrm{L})_{t+k} u_t; \tag{6}$$

which has a covariance matrix:

$$\Omega_{\mathrm{t+k}} = E[\mathbf{e}_{t+k}\mathbf{e}_{t+k}^{'}] = \mathrm{E}[\hat{\mathbf{A}}(\mathrm{L})_{t+k}\hat{\mathbf{A}}(\mathrm{L})_{t+k'}] \tag{7}$$

As in Diebold and Yilmaz (2009), the variance decomposition allows us to divide the forecast error variances of risk (NPL ratio) into parts attributable to shocks in the system. That is, given the error in forecast variance decomposition, the method permits to identify two types of diffusion elements in addition to the total variance due to news on that period. First, the fraction of the *k-periods-ahead* variance of the error in forecasting the risk of bank j that is due to the bank's own shocks; and second, the amount of error variance of bank j that is due to the indirect transmission of shocks from other banks. These two contributing factors are what we define as the diffusion process of risk among banks.

Diebold and Yilmaz (2009) construct and define the *own variance shares* and *cross variance shares (or diffusion)*. In our case, these two elements are the fractions of the $k-step-ahead$ error variance in forecasting each bank's risk due to its own shocks and due to other banks risk, respectively. To illustrate the above description, consider the k-periods forward Cholesky matrix of J banks in the VAR system to be:

$$\hat{\mathbf{A}}(\mathrm{L})_{t+k} = \begin{bmatrix} a(L)_{1,1} & \dots & a(L)_{1,J} \\ \vdots & \ddots & \vdots \\ a(L)_{J,1} & \dots & a(L)_{J,J} \end{bmatrix}_{\mathrm{t+k}} \tag{8}$$

where $\mathbf{e}_{t+K} = \hat{\mathbf{A}}(\mathrm{L})_{t+k}\mathbf{u_t}$ is defined by equation (6).

The corresponding error in the variance of the forecast for k-periods forward risk for each bank j is therefore defined by the $[\omega_{j,j}]_{t+k}$ element of the covariance matrix:

$$[\omega_{j,j}]_{t+k} = \sum_{m=1}^{J} [a(L)^2_{j,m}]_{t+k} \tag{9}$$

As mentioned before, the decomposition of the error in variance permit us to identify the diffusion, which then gives way to estimate $J \times (J-1)$ possible spillover effects. That is, it requires to calculate the effect of shocks in each of the J banks on every other bank in the system, of which there are $(J-1)$-many. For instance, we identify from this example that the error in variance for bank j of the predicted risk $[\omega_{(j,j)}]_{(t+k)}$ is indirectly affected by each of the shocks in risk for the $m \neq j$ banks through the $[a(L)^2_{j,m}]_{t+k}$ elements of the $\hat{\mathbf{A}}(\mathrm{L})_{t+k}$ matrix.

We use the diffusion decomposition to measure each of the individual bank's contribution to the risk of the other banks in the system. These diffusion contributions are the basis for the construction of the spillover index, and they are drawn from the $[a(L)^2_{j,l}]_{t+k}$ elements of the $A(L)_{t+k}$ matrix to build the Diebold-Yilmaz spillover index.

Finally, the overall spillover index over an $L-th$ lag order and J-variables VAR using*K-periods-ahead* forecasting is computed as:

$${}_{\mathrm{k}}\mathrm{S} = \frac{\sum_{k=0}^{K-1} \sum_{\substack{i,\, j\, =\, 1 \\ i \neq j}} [a(L)^2_{t+k}]}{\sum_{k=0}^{K-1} (\hat{\mathbf{A}}(\mathrm{L})_{t+k} \hat{\mathbf{A}}(\mathrm{L})_{t+k}{}')} \times 100 \tag{10}$$

The index ${}_{\mathrm{k}}\mathrm{S}$ shows the ratio of the sum of the contributions of each of the J banks to the total variation of the error forecast for bank j relative to the total variation of the error forecast for k periods ahead. Hence, the spillover index identifies and measures the cross variance share of the total variance over the *k-step-ahead* prediction of the risk of bank j relative to the whole variation of the error in prediction. In our analysis, we construct this index using different forecast periods ahead (k) to identify the relative importance of diffusion of risk as we increase the length of prediction of any bank NPL ratio across banks, and in all the banking system.

4. The Mexican Banking System (2002 - 2013) and the Data

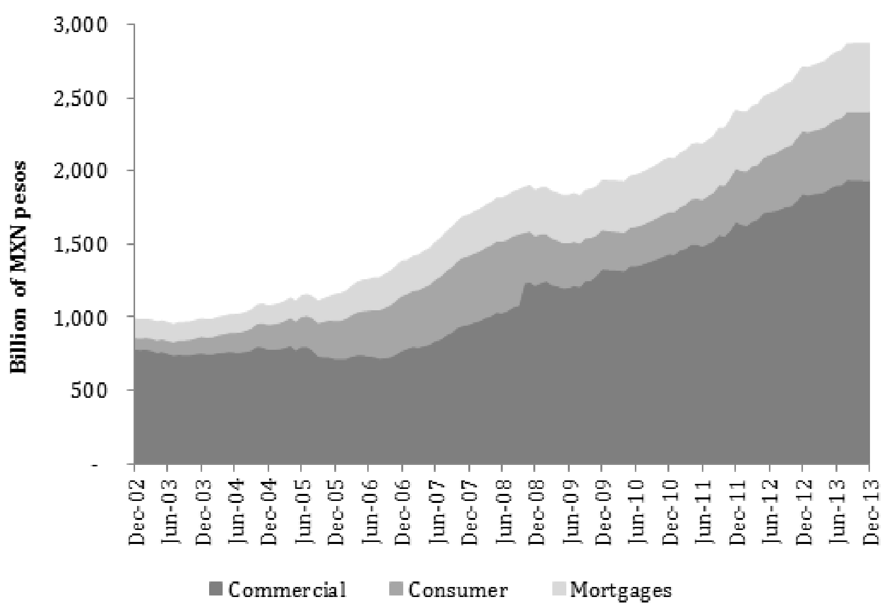
The Mexican banking system has faced several structural changes since the 1980s; it went from nationalization in 1982, to privatization in 1991, to a very severe crisis in 1995. Credit markets stayed almost closed for nearly all of the 1980s and during the second half of the 1990s. In the aftermath of the 1995 crisis, the most feasible way to recapitalize the banks was to modify banking regulations to allow foreign direct investment and foreign control of Mexican banks. The internationalization process of the institutions, which lead to the market structure that is present today, started in 1997 and concluded during the first half of the 2000s. Multinational banks like Citibank, HSBC, BBVA, Bank of Nova Scotia, and Santander acquired control of all major institutions between 1997 and 2002;[3] by 2005, the midpoint of the decade, 83 percent of bank assets

[3] The main exception was Banorte that remains under Mexican investors' control. It is currently the third largest bank in the country after the recent acquisition of Banco Ixe.

and 82 percent of deposits were controlled by foreign institutions. With new international players, the writing-off process of past-due loans, derived from the crisis of the 1990s, was concluded. Banks' new owners wanted healthy balance sheets to fully restore the credit granting business.

Our period of study covers from the 2000 decade until 2013. There are two clearly defined stages within that period of time. The first between 2000 and 2005 in which the credit market concluded its contraction process as the newly issued credit did not offset the loans that were being written off. The second period is from 2006 to 2013 where the credit growth rates became positive and high, slowing down only during the economic turmoil in 2008-2009. We present the evolution of credit balances during the whole period in Figure 1, where we observe that the value of the consumer portfolio increased by more than 6 times (annual growth rate close to 16 percent in real terms). Mortgage loans and commercial loans portfolios had an average of 7.8 and 11 percent real annual growth rates, increasing their value 3.8 and 2.5 times respectively.

Figure 1. Evolution of Monthly Total Balance by Type of Credit (Dec 2002 - Dec 2013).



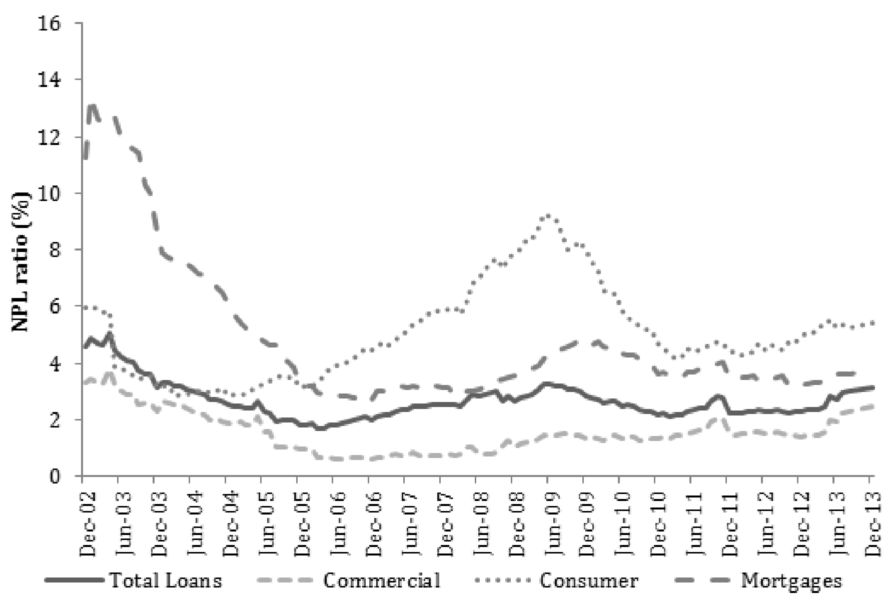
Source: National Banking and Securities Commission (Mexico).

As the structure of the banking system did not suffer any other structural break after 2002 our period of study is between December 2002 and September 2013. As mentioned before the variable of interest to assess the dynamics of credit risk is the NPL ratio.[4] The data consist of a balanced panel with end-of-the-month balances of total loans and credit portfolios for the 18 largest banks in

[4] We also estimated all models using the ratio of loan loss provisions (LLP) to total loans

Mexico, and 132 monthly observations.[5] All data were obtained from the web page of the National Banking and Securities Commission (Comisión Nacional Bancaria y de Valores, CNBV) that releases monthly balance sheets and income statement for all supervised banks in Mexico. Using the data on total loans and non-performing loans, we calculate the NPL ratio for each month and each bank in the sample for the total credit portfolio as well as for the commercial loans, mortgage loans and consumer loans portfolios. The selection of banks is based on data availability, as we include only those institutions that operated during the whole period. In any case, these 18 banks represented the 92 percent of the total credit market in Mexico in December 2002, and as of December 2013, they represent the 95 percent of the market. Figure 2 presents the evolution of the NPL ratio for the Mexican Banking System over the studied period. After December 2002 there is a sharp decline in the ratio, which is mainly induced by an aggressive writing-off process of past due loans originated during the crisis as previously mentioned. It can also be seen that the NPL ratio for all types of loans started to increase again during 2008 and 2009 as a consequence of the financial crisis in the United States, which induced a recession period in the Mexican economy as well. The most affected portfolio was consumer loans.

Figure 2. Monthly NPL Ratio Dynamics by Type of Credit and for Total Loans (Dec 2002-Dec 2013).



instead of the NPL ratios since LLP can be considered a more forward looking measure of credit risk. All results remained qualitatively the same compared to those presented in this document. Results with LLP are available from the authors upon request.

[5] Afirme, American Express Bank, Banco Azteca, Banco del Bajío, Banamex, Banregio, Bansi, BBVA Bancomer, Banorte, HSBC, Inbursa, Interacciones, Invex ,Ixe, Mifel, Monex, Santander and Scotiabank.

Source: National Banking and Securities Commission.

To control for risk factors and for a potential channel of contagion, we use monthly total loans growth rate, the log of total assets as a proxy for bank size, and the percentage of interbank loans to total loans. It can be expected that smaller banks will take higher risks than large banks; high credit growth rates may indicate increasing risk taking or lower credit standards, and banks more exposed to the interbank market could be more vulnerable to contagion from other institutions. First, we estimate the VAR models including these exogenous variables one by one to test them individually, and then we create one specification including all three controls. Table 1 presents summary statistics for all variables used in VAR specifications.

Table 1. Sample Statistics (Dec 2002 - Dec 2013)

	NPL ratio Total Loans (%)						NPL ratio Commercial Loans (%)					
	Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque		Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque	
Afirme	2.68	1.61	0.30	-1.32	11.4	**	2.08	1.15	0.58	-0.45	8.3	**
American Express	4.82	2.50	1.07	-0.30	25.2	**	NA	NA	NA	NA	NA	
Azteca	5.73	3.26	0.43	-0.50	5.4		1.26	1.70	4.90	35.47	6656.7	**
Bajio	2.20	0.88	-0.19	-1.26	9.4	**	1.55	0.57	0.06	-1.34	9.8	**
Banamex	2.72	2.13	0.84	-0.79	18.7	**	2.02	2.95	1.26	-0.12	34.6	**
Banregio	1.82	0.53	-0.03	-1.01	5.6		1.35	0.62	0.69	0.29	10.8	**
Bansi	2.59	1.27	2.54	13.69	1155.2	**	1.35	0.53	0.69	-0.45	11.4	**
BBVA	2.92	0.94	0.42	-0.18	4.0		2.56	1.33	2.36	11.81	875.5	**
Banorte	1.92	0.42	0.74	-0.36	12.5	**	1.28	0.87	0.30	-1.31	11.3	**
HSBC	4.04	1.96	1.94	4.57	194.9	**	2.54	1.77	2.20	4.60	219.7	**
Inbursa	1.99	1.11	0.28	-0.88	5.9		1.84	1.11	0.37	-1.03	8.7	**
Interacciones	1.19	1.45	2.38	4.85	250.3	**	1.13	1.42	2.40	5.03	261.9	**
Invex	2.49	1.38	0.90	-0.11	17.5	**	1.36	0.54	0.61	0.40	9.0	**
Ixe	0.94	0.60	0.65	-0.62	10.9	**	0.79	0.64	0.72	-0.76	13.7	**
Mifel	2.63	0.98	0.58	-0.29	7.7	**	2.42	0.96	0.68	-0.52	11.6	**
Monex	2.31	3.51	4.05	16.57	1843.1	**	2.41	3.51	3.99	16.22	1770.0	**
Santander	0.98	0.44	1.34	1.97	60.2	**	0.53	0.32	1.94	4.22	177.8	**
Scotia	3.16	0.96	1.03	0.49	24.3	**	1.28	0.59	0.76	-0.05	12.5	**

Table 1. Sample Statistics (Dec 2002 - Dec 2013) (continued).

	NPL ratio Consumer Loans (%)						NPL ratio Mortgages Loans (%)					
	Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque		Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque	
Afirme	6.35	2.05	0.21	-0.84	4.8		4.93	4.32	0.60	-1.08	14.3	**
American Express	4.84	2.50	1.08	-0.29	25.6	**	NA	NA	NA	NA	NA	
Azteca	6.93	3.75	0.15	-0.73	3.3		8.75	6.68	-0.05	-1.52	11.9	**
Bajio	3.81	1.42	-0.42	0.81	7.3	**	7.50	3.83	-0.57	0.02	7.0	**
Banamex	4.07	1.26	1.50	2.40	80.0	**	3.33	1.93	0.64	-0.73	11.8	**
Banregio	4.28	1.78	0.90	0.26	18.0	**	2.34	2.15	0.28	-1.67	16.9	**
Bansi	4.77	1.79	-0.39	-0.51	4.7		NA	NA	NA	NA	NA	
BBVA	7.11	5.13	1.59	2.20	80.8	**	5.37	3.15	1.74	2.55	100.6	**
Banorte	4.80	1.55	1.26	1.60	48.3	**	2.99	2.45	2.03	5.03	226.4	**
HSBC	6.23	3.98	1.39	0.98	47.1	**	7.93	3.89	1.48	2.16	72.7	**
Inbursa	3.68	2.67	0.35	-0.79	6.0		7.79	3.14	-0.61	-0.12	8.2	**
Interacciones	7.96	6.42	0.52	-0.31	6.4	**	5.48	2.06	1.17	1.14	36.6	**
Invex	NA	NA	NA	NA	NA		NA	NA	NA	NA	NA	
Ixe	2.90	1.27	0.63	0.48	9.6	**	2.73	2.29	2.42	5.58	284.3	**
Mifel	10.41	8.32	0.47	-0.76	5.1		4.18	4.25	0.74	-0.86	13.2	**
Monex	NA	NA	NA	NA	NA		NA	NA	NA	NA	NA	
Santander	NA	NA	NA	NA	NA		2.39	1.29	1.98	3.58	154.1	**
Scotia	3.67	2.03	0.30	-0.66	4.3		6.30	4.69	2.40	4.81	249.9	**

Table 1. Sample Statistics (Dec 2002 - Dec 2013)
(continued).

	Total Assets (Size), billions of MXN						Total loans growth (%)					
	Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque		Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque	
Afirme	43	31	0.87	-0.74	19.45	**	-1.17	45.01	-1.07	12.37	846.8	**
American Express	11	5	-0.49	-1.27	13.84	**	-1.17	9.23	-0.79	1.04	19.3	**
Azteca	53	25	-0.41	-0.68	6.22	**	-3.13	32.55	-3.90	25.60	3847.8	**
Bajio	61	28	0.03	-0.98	5.21		-2.05	12.49	0.03	7.87	333.2	**
Banamex	851	226	-0.11	-1.58	13.74	**	-0.68	11.06	0.25	13.95	1047.2	**
Banregio	37	20	0.96	0.10	19.94	**	-1.80	9.02	-0.03	1.17	7.4	**
Bansi	13	3	-0.32	-0.32	2.72		-1.65	35.62	-1.13	2.52	61.9	**
BBVA	947	259	-0.23	-1.54	13.99	**	-0.79	2.47	0.24	1.22	9.3	**
Banorte	460	139	0.13	-0.75	3.44		-0.76	14.89	8.15	83.20	38639.1	**
HSBC	368	97	-0.23	-1.32	10.54	**	-0.38	5.37	0.83	2.91	60.3	**
Inbursa	168	54	0.07	-1.67	15.22	**	-1.14	14.54	0.44	2.60	40.6	**
Interacciones	48	32	0.26	-1.31	10.84	**	-2.38	41.05	-0.52	1.99	27.2	**
Invex	22	12	0.26	-0.56	3.15		-0.73	39.90	-1.79	16.23	1485.2	**
Ixe	48	31	0.27	-1.20	9.31	**	-1.72	24.58	-0.02	1.12	6.5	**
Mifel	24	10	-0.01	-1.41	10.70	**	-1.27	25.61	-0.95	2.33	48.5	**
Monex	15	16	1.08	0.01	25.31	**	-0.52	314.52	4.41	38.25	8283.7	**
Santander	575	208	-0.95	-0.17	19.82	**	-1.30	41.62	-8.78	91.37	46527.5	**
Scotia	166	29	-0.02	-0.24	0.33		-0.75	3.73	-0.29	5.49	163.8	**

Table 1. Sample Statistics (Dec 2002 - Dec 2013)
(continued).

	Interbank loans to total loans (%)					
	Mean	St. Dev.	Skew.	Kurt.	Bera-Jarque	
Afirme	3.55	4.04	4.15	24.32	3577.0	**
American Express	NA	NA	NA	NA	NA	
Azteca	0.03	0.20	6.51	41.36	10183.2	**
Bajio	6.14	3.65	0.92	0.18	18.4	**
Banamex	12.44	7.18	0.80	-0.27	14.3	**
Banregio	4.76	4.21	0.66	-0.94	14.2	**
Bansi	0.04	0.13	3.75	13.60	1306.5	**
BBVA	1.84	1.04	0.47	0.18	4.9	
Banorte	4.41	2.28	0.74	-0.76	15.0	**
HSBC	4.25	1.91	0.73	-0.42	12.4	**
Inbursa	6.48	3.82	0.48	-0.55	6.6	**
Interacciones	7.00	8.30	1.19	-0.06	30.5	**
Invex	11.34	5.74	-0.13	-1.15	7.5	**
Ixe	18.13	7.76	-0.04	-0.11	0.1	
Mifel	8.40	5.98	1.44	0.94	49.4	**
Monex	24.30	24.24	1.55	1.22	60.2	**
Santander	8.86	8.97	0.21	-1.91	20.6	**
Scotia	4.57	2.43	1.20	0.06	31.0	**

Source: National Banking and Securities Commission (CNBV, Mexico)

Note: Numbers are summary statistics for monthly NPL ratio for each bank by type of credit, total assets (billions of MXN pesos), loan growth rates in percentage and the percentage of interbank loans to total loans, from December 2002 to December 2013. NPL ratio divides the NPL balance reltive to total loans. JB is the Jarque-Bera test for the null hypothesis of normal distribution. * and ** indicate significance at the 5% and 1% levels, respectively.

5. Estimation and Results

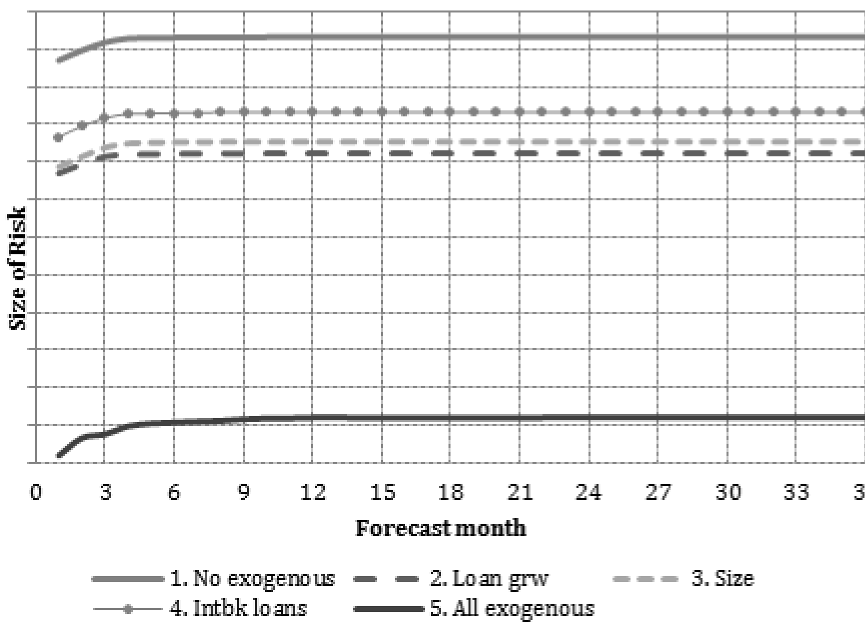
In our first approach we use five VAR specifications to estimate the determinant of the variance-covariance matrix of errors and the spillover index, for the total loan portfolio and for several forecast horizons. We use two lags for the VAR process based on the Akaike Information criterion (AIC) and to address the non-stationarity we introduce all data in first differences or percentage ratios. Compared to Diebold & Yilmaz (2009), who use a 10-day forecast period spillover for rolling-over windows to assess how the index changes over time, we fix the sample starting point (December 2002) and progressively change the forecast period from one to 36 months.[6] This method allows us to determine how long does it takes for the credit risk to spread throughout the whole system, and how the size of risk coming from other banks, and the relevance of the spillover effect, evolve over time.

a. The Size of Risk of Innovations

To estimate the size of risk in the system due to innovations, we calculate the determinant of the error in the variance-covariance matrix for each of the k-steps ahead and for each one of the 5 specifications. We define the aggregate contribution of news to total risk in the system in terms of the determinant of the variance-covariance matrix to allow for comparisons over forecast periods and between models. Figure 3 presents graphically our measures of size of risk for each model and for 1 to 36 forecast periods. The first model does not include any exogenous variables; model 2 uses loan growth ratio, model 3 controls for size measured as the log of total assets, model 4 considers the percentage of interbank loans to total loans, and the fifth model includes all three exogenous variables. We notice in figure 3 that the size of risk due to forecast errors in 1 to 3 forecasted periods is slightly below the size of the risk afterwards. In all cases the size of risk stabilizes from the fourth forecasted period, indicating that there may be a long-run level of risk in the system. Also, in the long term the size of risk from innovations is higher.

[6] In our first estimations we used forecast periods up to 60 months, however, as we will comment below, the value of the index stabilizes around 12 months and after that changes in the value of the spillover are negligible. Presenting results for 36 months correctly illustrates the process and the long run equilibrium.

Figure 3. Size of Risk in the System due to Innovations by 5 Different Specifications, using Monthly Changes in Banks' NPL Ratio as Proxy for Credit Risk.



Size is measured with the determinant of the variance-covariance matrix of forecast errors. Model 1 does not include exogenous variables; model 2 uses loan growth ratio, model 3 controls for size measured as the log of total assets, model 4 considers the percentage of interbank loans to total loans, and the fifth model includes all three exogenous variables. The variance decomposition uses a monthly VAR of order 2. Lag-order is defined using AIC. Forecast periods are from 1 to 36 months.

As expected, the magnitude of the risk arising from innovations in each bank depends on the number of control variables that we include in the VAR estimation. The more we control for individual sources of risk, the lower is the importance of individual innovations on the risk in the system. Models that control more for individual factors result in lower magnitude of variance of forecast errors. That is, the value of the determinant of the variance-covariance matrix is lower as we increase the number of control variables. We interpret the results as evidence that bank size, credit portfolio expansion and the exposure to interbank loans explain the degree of credit risk in banks. For this reason the observed level of risk due to individual shocks is lower applying those controls.

b. The Spillover Index

Given that the size of risk in the system is not equal in all models the next step is to determine through the spillover index how much of the risk in the system -as proportion of total risk- can be attributed to contagion from innovations in each bank. Table 2 presents the results of the spillover index, the decomposition of the index among banks and their contribution to the NPL ratio (credit risk) of other institutions, using a forecast window of 36 months. We present results following the format of Diebold & Yilmaz (2009). In each cell in the table (*bank i*, *bank j*), we find the estimated contribution to the forecast error variance of bank i coming from shocks in bank j. The sum of the column elements, excluding the "diagonal" entry (own contribution to the forecast error variance), plus the sum of row elements, also excluding the bank's own contribution, provides the numerator of the spillover index. The sum of all of the elements, including the bank's own contributions, is the spillover index denominator. Finally, the bottom right of each table contains the estimated spillover index for the corresponding model.

Panel A from Table 2 shows that the spillover index is 38.6 percent when we do not include any control variable; controlling for size, loan growth and the percentage of interbank loans, the spillover index becomes 78.6 percent (Panel E). Interestingly, the spillover effect accounts for a higher proportion of total risk in the system when we include control variables in the VAR specification, despite that the size of the influence of individual innovations on total risk diminishes as previously noted. These results show that, once we control for intrinsic sources of risk the spillover effect, or common sources of risk, account for a greater proportion of total risk, and individual sources become less important. This fact is also observed in the last column in each panel that presents the percentage of error variance that is explained by other banks (for example, all numbers in last column of Panel E are larger than the corresponding numbers in Panel A).

Although all panels provide a decomposition of the spillover index presenting the percentage of variance error explained by the corresponding institution, we cannot derive conclusions about the causal relations of the shocks among institutions. Recall that VAR estimations are sensible to data input ordering and therefore the first institution entering the model will be the one with lower level of contagion from other banks. However we can derive conclusions about the patterns between the five panels that remain unaffected even when we change the data input order.[7] For example, the percentage of error variance of Afirme explained by other banks is 16.2 percent in Panel A, and 61.3 percent in Panel E, implying that the increase in the percentages of contagion from other banks holds for all banks when we include control variables. Once again, controlling for internal sources of risk raises the relevance of external risks in explaining total risk.

[7] For the sake of robustness, we estimated the system using several randomly selected data series order. In every case, the forecasted error variance coming from the institution itself for the first bank in the sample results in the higher percentage in the table. In all cases the magnitude of the overall spillover index remained almost unchanged.

Table 2. NPL Ratios Spillover Index, Total Loans with Control Variables (36 Forecast Periods)

Panel A. Model 1, no exogenous variables	Afirme	Amex	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Invex	Ixe	Mifel	Monex	Stander	Scotia	From Others
Afirme	83.76	1.29	1.43	1.70	0.60	0.35	0.85	0.66	0.21	0.61	0.91	0.99	2.56	2.43	0.64	0.45	0.15	0.40	16.2
American Express	6.80	68.93	2.77	0.19	1.02	5.78	0.63	2.80	1.95	1.75	1.05	3.16	0.48	0.11	0.40	0.27	0.73	1.18	31.1
Azteca	5.24	1.57	78.66	0.10	0.92	0.27	1.12	0.72	0.50	0.31	1.29	1.17	0.19	0.62	0.85	4.19	0.73	1.56	21.3
Bajio	1.41	1.74	5.64	75.85	1.99	1.70	1.08	0.76	0.24	0.68	3.31	1.48	0.83	0.93	0.70	0.51	0.92	0.20	24.2
Bnamex	13.23	3.19	1.23	2.49	62.52	2.10	0.30	1.14	0.28	1.07	4.27	2.46	2.18	0.64	0.34	0.47	1.58	0.51	37.5
Bregio	9.11	1.23	0.65	1.53	0.44	73.64	0.30	0.85	0.78	1.52	1.11	0.96	1.19	0.51	3.15	1.14	0.52	1.37	26.4
Bansi	4.67	1.27	1.97	1.18	1.15	3.79	55.46	8.73	1.45	1.06	0.27	8.95	1.59	1.21	2.15	0.88	0.80	3.43	44.5
BBVA	4.26	4.14	2.52	1.60	0.96	1.95	2.57	56.86	4.94	4.86	2.03	0.77	1.46	3.91	1.77	1.26	2.24	1.90	43.1
Banorte	3.97	1.90	1.29	3.20	0.61	4.74	3.03	4.20	57.61	1.14	2.32	0.54	0.73	5.73	2.52	1.90	3.51	1.07	42.4
HSBC	0.63	4.58	1.63	2.88	2.20	3.27	1.76	12.17	2.85	62.80	0.40	1.73	0.19	0.53	0.90	0.52	0.61	0.35	37.2
Inbursa	1.89	0.86	6.31	4.56	1.02	1.94	2.48	1.19	2.58	2.34	61.56	2.47	2.60	0.24	3.05	1.28	3.08	0.56	38.4
Interacc	9.69	0.90	1.66	7.29	2.24	6.02	22.10	4.28	1.52	1.52	1.41	36.85	0.91	1.25	0.50	0.42	0.58	0.86	63.2
Invex	1.53	0.62	12.25	2.24	2.53	1.18	3.01	1.50	0.93	1.52	3.10	2.40	61.43	0.28	0.63	0.69	3.92	0.24	38.6
Ixe	2.44	2.04	3.06	4.16	1.55	2.17	0.85	6.28	2.40	11.91	3.63	2.09	1.18	50.78	1.54	1.18	1.77	0.97	49.2
Mifel	3.78	3.87	3.45	4.56	1.51	3.28	1.80	1.59	3.69	1.93	2.70	1.56	1.44	0.21	61.53	1.21	1.10	0.76	38.5
Monex	2.50	0.04	6.48	12.20	0.66	0.60	0.28	0.70	0.73	0.92	1.03	3.44	1.48	1.47	1.32	65.36	0.23	0.56	34.6
Stander	0.17	1.49	13.50	0.78	3.37	1.76	8.11	2.42	1.80	0.65	3.23	4.80	2.52	0.54	1.00	1.61	51.77	0.47	48.2
Scotia	5.36	7.37	1.27	4.49	3.46	2.11	1.78	2.57	1.20	4.50	1.99	11.87	4.27	0.74	2.24	1.23	3.67	39.87	60.1
Contrib. to others	76.7	38.1	67.1	55.2	26.2	43.0	52.0	52.6	28.1	38.3	34.0	50.8	25.8	21.4	23.7	19.2	26.1	16.4	694.8
Contrib. including own	160.4	107.0	145.8	131.0	88.8	116.6	107.5	109.4	85.7	101.1	95.6	87.7	87.2	72.1	85.2	84.6	77.9	56.3	**38.6%**

Panel B. Model 2, loan growth as exogenous variable	Afirme	Amex	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Invex	Ixe	Mifel	Monex	Stander	Scotia	From Others
Afirme	71.04	1.40	0.81	0.54	1.09	0.55	0.50	0.73	0.92	2.93	2.67	1.13	2.30	11.03	0.61	0.75	0.75	0.25	29.0
American Express	3.80	71.39	2.50	0.90	2.87	4.16	1.88	0.36	1.68	1.64	1.55	2.47	0.76	0.65	0.62	0.73	0.46	1.58	28.6
Azteca	5.09	5.25	64.69	1.08	0.99	0.75	1.09	0.54	2.96	0.68	3.43	0.47	0.57	0.98	3.05	3.54	1.89	2.96	35.3
Bajio	2.01	4.23	4.39	70.78	0.37	1.27	0.75	1.07	2.16	1.09	0.92	1.98	0.72	2.38	3.15	1.11	1.01	0.59	29.2
Bnamex	8.87	7.25	4.39	1.00	56.20	2.07	0.62	2.38	0.50	2.51	3.25	1.24	1.80	2.94	0.47	0.72	2.38	1.39	43.8
Bregio	4.72	0.54	1.81	1.39	1.64	77.86	0.50	0.62	1.24	1.10	0.71	0.16	1.31	1.29	1.91	1.11	1.62	0.48	22.1
Bansi	6.09	1.72	1.22	1.58	0.94	4.14	54.97	8.91	1.51	1.51	0.93	6.94	2.25	1.23	2.34	0.86	0.13	2.73	45.0
BBVA	3.94	5.43	2.20	1.24	0.42	1.47	2.54	54.72	3.66	6.67	3.99	1.37	1.03	2.16	5.13	1.26	1.94	0.84	45.3
Banorte	2.56	1.14	1.34	5.66	0.36	6.87	3.28	4.53	56.59	2.82	2.32	0.31	0.97	3.44	1.89	1.28	3.51	1.12	43.4
HSBC	1.31	5.84	2.49	2.60	0.59	3.74	1.40	8.63	5.02	56.69	0.84	1.66	0.24	0.45	3.09	0.67	3.66	1.08	43.3
Inbursa	0.77	1.98	6.12	15.96	0.67	2.39	1.17	2.85	1.86	3.98	51.69	1.55	2.82	2.26	1.09	0.51	1.70	0.65	48.3
Interacc	7.37	2.43	3.15	2.89	1.46	9.39	20.77	6.49	2.25	1.38	4.89	29.12	1.26	2.77	1.45	1.40	0.60	0.93	70.9
Invex	1.58	0.97	12.53	1.71	2.77	2.00	5.18	0.93	1.10	4.34	4.48	2.01	47.74	1.93	0.82	2.52	6.47	0.91	52.3
Ixe	2.90	4.57	2.17	2.35	0.52	2.34	1.09	5.66	6.03	12.02	2.62	1.66	0.82	47.88	3.10	0.90	1.84	1.52	52.1
Mifel	6.00	3.63	2.80	3.58	2.58	1.13	2.13	1.57	3.20	2.23	2.93	0.88	1.57	0.73	61.00	2.27	0.79	0.97	39.0
Monex	0.70	0.14	5.39	8.59	1.91	0.94	0.10	1.15	1.45	0.36	1.10	3.85	5.01	1.28	2.30	64.61	0.63	0.48	35.4
Stander	1.41	2.10	9.20	1.14	2.39	1.74	12.00	1.67	1.11	1.77	4.02	6.95	4.05	2.50	2.39	1.97	42.64	0.95	57.4
Scotia	1.66	6.83	1.95	4.20	3.52	3.30	2.98	2.34	1.14	8.32	4.91	11.89	2.25	4.05	2.82	1.87	0.53	35.41	64.6
Contrib. to others	60.8	55.5	64.5	56.4	25.1	48.2	58.0	50.4	37.8	55.4	45.6	46.5	29.8	42.1	36.2	23.5	29.9	19.4	785.0
Contrib. including own	131.8	126.8	129.2	127.2	81.3	126.1	112.9	105.2	94.4	112.0	97.3	75.7	77.5	89.9	97.2	88.1	72.6	54.8	**43.6%**

Panel C. Model 3, size (log total assets) as exogenous variable	Afirme	Amex	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Invex	Ixe	Mifel	Monex	Stander	Scotia	From Others
Afirme	74.22	1.07	0.82	1.40	1.26	1.15	1.11	2.84	0.52	0.34	2.36	2.60	3.61	3.72	1.09	0.98	0.16	0.76	25.8
American Express	9.55	52.61	2.09	1.62	5.77	8.71	1.66	4.95	1.05	1.64	0.83	2.87	1.07	0.23	1.30	0.43	1.33	2.28	47.4
Azteca	3.41	1.00	78.96	0.54	1.24	0.82	0.64	0.78	0.44	0.48	1.06	1.42	0.82	0.60	1.50	2.13	1.56	2.60	21.0
Bajio	1.43	4.11	10.91	57.20	0.64	2.99	0.53	1.98	0.92	3.16	3.95	1.82	1.45	0.71	2.84	2.49	1.24	1.63	42.8
Bnamex	16.75	5.03	1.36	3.87	47.68	1.86	0.69	3.13	0.59	0.86	5.48	5.41	2.63	1.32	0.56	0.63	0.83	1.33	52.3
Bregio	10.25	0.69	1.29	2.19	0.78	64.41	1.09	2.65	0.19	2.57	1.58	1.42	2.07	0.92	3.43	1.42	1.36	1.70	35.6
Bansi	3.59	3.72	1.72	1.60	1.38	5.42	54.03	10.22	0.93	0.42	1.04	6.69	2.17	1.10	1.82	0.45	0.93	2.77	46.0
BBVA	4.44	9.82	9.55	2.15	2.51	3.36	2.54	44.60	4.66	1.52	3.97	0.77	2.36	2.51	1.11	1.11	1.64	1.36	55.4
Banorte	4.72	2.36	9.52	3.54	3.57	9.86	1.72	6.13	38.29	1.07	1.74	0.94	0.80	6.37	3.13	2.79	1.21	2.23	61.7
HSBC	0.80	1.84	6.01	2.00	1.20	3.45	2.99	9.39	7.19	51.16	1.18	2.01	0.59	3.19	1.18	0.84	1.90	3.07	48.8
Inbursa	1.79	1.12	10.79	8.34	1.48	2.03	2.29	2.57	0.92	4.38	47.11	2.59	1.28	1.32	3.60	2.87	4.33	1.18	52.9
Interacc	9.81	1.25	2.54	5.39	1.54	8.51	31.76	4.70	1.95	1.77	1.51	24.59	1.61	1.58	0.23	0.29	0.47	0.48	75.4
Invex	2.04	1.13	7.29	1.48	1.70	2.95	5.13	1.26	0.81	3.52	6.86	4.16	53.24	1.15	1.14	1.30	2.54	2.29	46.8
Ixe	4.24	2.21	3.60	2.12	3.24	4.18	1.97	4.45	1.60	8.64	7.37	1.83	1.33	47.52	3.14	0.83	0.39	1.33	52.5
Mifel	2.42	3.28	4.00	4.64	2.96	4.05	2.95	0.45	1.83	2.53	6.71	2.57	2.06	0.89	53.02	0.62	2.94	2.10	47.0
Monex	2.67	0.69	11.73	9.72	0.29	1.93	0.42	1.54	2.39	2.25	1.80	2.35	0.66	1.59	1.70	55.65	0.28	2.34	44.4
Stander	1.69	2.64	5.49	1.07	1.55	3.72	12.49	5.72	2.78	3.20	3.82	4.34	0.77	1.01	1.46	2.15	45.04	1.07	55.0
Scotia	8.34	4.73	4.12	7.35	3.74	4.19	5.83	2.55	1.03	2.59	1.70	10.69	2.73	1.82	3.41	1.96	2.57	30.64	69.4
Contrib. to others	87.9	46.7	92.8	59.0	34.9	69.2	75.8	65.3	29.8	40.9	53.0	54.5	28.0	30.0	32.6	23.3	25.7	30.5	880.0
Contrib. including own	162.2	99.3	171.8	116.2	82.5	133.6	129.8	109.9	68.1	92.1	100.1	79.1	81.2	77.6	85.7	78.9	70.7	61.2	**48.9%**

Table 2. NPL Ratios Spillover Index, Total Loans with Control Variables (36 Forecast Periods) continued

Panel D. Model 4, interbank loans as exogenous variable

	Afirme	Amex	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Invex	Ixe	Mifel	Monex	Stander	Scotia	From Others
Afirme	70.83	1.49	1.29	2.62	1.24	0.41	1.00	2.54	1.46	3.59	0.94	2.14	4.31	1.90	0.14	2.44	1.02	0.65	29.2
American Express	3.69	54.25	4.11	2.48	3.02	1.05	3.82	8.10	1.56	4.19	0.94	0.43	1.50	2.03	1.48	1.65	3.90	1.80	45.7
Azteca	4.60	3.77	63.07	2.81	1.81	0.66	2.53	4.14	1.79	2.65	2.07	1.08	1.44	1.63	1.07	3.18	0.97	0.72	36.9
Bajio	0.97	3.35	7.38	62.85	2.21	0.26	1.99	1.25	1.60	1.06	2.99	2.01	0.97	3.60	0.50	2.70	2.91	1.40	37.2
Bnamex	10.90	20.24	0.48	1.20	40.67	0.64	7.79	1.70	1.04	1.46	4.64	1.37	1.44	1.85	0.18	1.69	0.83	1.88	59.3
Bregio	13.78	1.25	4.45	5.50	0.63	49.07	2.73	2.36	2.25	4.74	1.48	1.07	1.17	2.52	1.16	4.45	0.79	0.61	50.9
Bansi	12.62	1.73	3.08	2.48	1.28	1.85	54.38	1.35	1.40	5.72	2.44	0.76	1.37	3.13	2.21	1.10	1.34	1.78	45.6
BBVA	6.30	14.92	4.77	3.53	1.93	3.18	4.06	46.55	3.24	1.61	2.55	0.54	0.74	1.37	0.62	1.49	2.04	0.57	53.4
Banorte	9.02	7.91	1.04	1.35	2.62	2.59	4.95	6.00	52.41	0.33	1.14	1.34	0.52	1.44	2.03	2.76	1.69	0.87	47.6
HSBC	2.00	12.05	1.15	6.37	4.01	3.77	1.26	3.28	0.58	58.35	0.48	0.56	0.27	1.67	0.17	0.96	1.25	1.82	41.7
Inbursa	4.39	3.23	1.68	7.94	1.80	6.59	3.79	4.66	1.77	2.72	43.59	0.68	3.23	0.49	2.42	4.29	1.88	4.86	56.4
Interacc	4.70	1.01	4.79	3.53	4.54	16.90	5.35	1.56	5.46	7.38	0.76	35.74	1.31	0.42	1.89	3.10	1.08	0.49	64.3
Invex	2.82	2.45	11.01	4.53	3.36	0.51	1.26	2.99	3.13	3.40	2.91	1.27	51.18	0.94	1.16	0.96	4.90	1.21	48.8
Ixe	1.98	1.74	4.08	5.12	4.61	5.05	2.98	0.71	3.10	2.12	4.61	2.80	2.26	52.65	1.68	0.82	2.20	1.49	47.4
Mifel	2.01	0.86	6.10	2.58	0.67	3.14	1.52	2.61	5.01	2.02	2.25	1.05	1.89	0.38	56.13	6.22	1.79	3.79	43.9
Monex	3.67	3.12	1.76	2.37	3.73	0.78	4.22	4.01	2.60	0.96	2.07	2.44	2.57	2.52	2.69	58.53	0.18	1.77	41.5
Stander	2.74	5.72	9.74	1.33	4.89	5.09	1.83	3.60	1.91	3.37	0.99	2.21	0.82	3.03	2.14	4.90	43.62	2.07	56.4
Scotia	3.91	2.23	1.85	2.57	5.29	3.83	1.91	1.73	1.11	2.73	6.06	1.18	0.97	1.20	3.33	2.44	3.35	54.32	45.7
Contrib. to others	90.1	87.1	68.8	58.3	47.6	56.3	53.0	52.6	39.0	50.0	39.3	22.9	26.7	30.1	24.9	45.1	32.1	27.8	851.8
Contrib. including own	160.9	141.3	131.8	121.2	88.3	105.4	107.4	99.2	91.4	108.4	82.9	58.7	77.9	82.8	81.0	103.7	75.7	82.1	**47.3%**

Panel E. Model 5, loan growth, size (log total assets) and interbank loans as exogenous variables

	Afirme	Amex	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Invex	Ixe	Mifel	Monex	Stander	Scotia	From Others
Afirme	38.67	3.56	4.57	13.29	0.95	2.60	2.25	7.12	3.83	2.32	0.61	0.88	3.71	7.23	3.35	3.33	1.23	0.51	61.3
American Express	9.02	29.98	5.43	8.76	3.50	10.05	2.74	5.72	3.96	3.38	0.99	1.27	1.84	3.27	4.13	3.67	0.43	1.85	70.0
Azteca	12.16	6.10	22.61	15.91	1.56	2.26	2.17	8.62	6.84	1.01	0.58	0.64	1.91	4.54	4.52	6.33	0.55	1.69	77.4
Bajio	4.05	8.16	7.05	41.65	1.71	2.01	2.77	3.63	4.68	5.77	0.37	1.86	1.21	5.11	3.41	4.91	0.31	1.33	58.4
Bnamex	9.50	9.31	9.65	15.19	11.36	3.01	2.81	10.31	4.38	0.98	0.44	0.87	2.89	5.52	5.63	6.10	1.09	0.96	88.6
Bregio	4.06	5.49	7.19	6.26	1.62	45.73	2.24	6.62	2.40	3.13	1.37	2.29	1.26	6.01	1.19	1.04	0.59	1.51	54.3
Bansi	8.99	8.55	5.96	8.83	2.97	4.19	17.33	7.49	4.31	5.65	0.65	4.27	4.23	7.37	3.27	3.72	0.57	1.64	82.7
BBVA	9.75	9.51	12.06	17.62	0.85	4.28	2.87	13.68	6.85	1.59	0.25	0.50	2.38	5.85	5.35	5.68	0.60	0.34	86.3
Banorte	10.81	3.06	8.51	15.16	5.28	4.80	2.77	7.73	18.67	1.39	0.36	1.34	1.97	5.82	5.77	4.93	0.32	1.30	81.3
HSBC	5.84	5.33	4.03	8.50	2.91	1.70	6.30	3.99	9.99	29.29	0.20	1.80	1.54	6.99	2.19	4.28	3.29	1.82	70.7
Inbursa	14.60	5.26	6.69	23.24	2.23	3.21	1.29	8.10	7.22	2.24	3.02	0.68	2.37	4.18	4.66	6.81	3.41	0.80	97.0
Interacc	11.24	8.16	8.85	13.17	0.84	6.09	6.92	10.42	4.73	3.28	0.47	5.28	2.77	7.16	4.02	4.16	1.62	0.82	94.7
Invex	7.60	8.20	4.46	10.35	4.96	5.70	6.37	6.09	5.68	3.83	1.46	1.26	12.80	6.56	3.30	6.81	2.71	1.87	87.2
Ixe	10.06	9.51	5.32	13.10	3.64	3.80	2.85	6.87	3.84	5.47	0.33	1.08	4.87	18.36	3.37	4.13	1.73	1.65	81.6
Mifel	14.18	4.84	3.77	15.98	3.01	2.93	2.82	2.71	3.24	5.81	0.96	0.73	2.95	9.60	12.95	6.17	5.95	1.41	87.0
Monex	3.33	6.21	11.67	11.93	1.83	0.95	1.96	3.03	3.87	4.94	0.89	0.42	1.09	2.47	3.81	38.32	1.85	1.41	61.7
Stander	8.99	4.40	4.58	14.05	4.82	4.96	7.39	4.58	2.75	2.74	0.56	3.66	1.74	4.60	3.93	12.42	12.55	1.28	87.5
Scotia	7.81	7.17	8.21	15.39	2.04	4.74	2.62	7.98	4.71	4.02	1.35	2.83	2.61	8.46	3.28	3.90	0.68	12.20	87.8
Contrib. to others	152.0	112.8	118.0	226.7	44.7	67.3	59.1	111.0	83.3	57.6	11.8	26.4	41.3	100.8	65.2	88.4	26.9	22.2	1415.5
Contrib. including own	190.7	142.8	140.6	268.4	56.1	113.0	76.5	124.7	102.0	86.9	14.9	31.7	54.1	119.1	78.2	126.7	39.5	34.4	**78.6%**

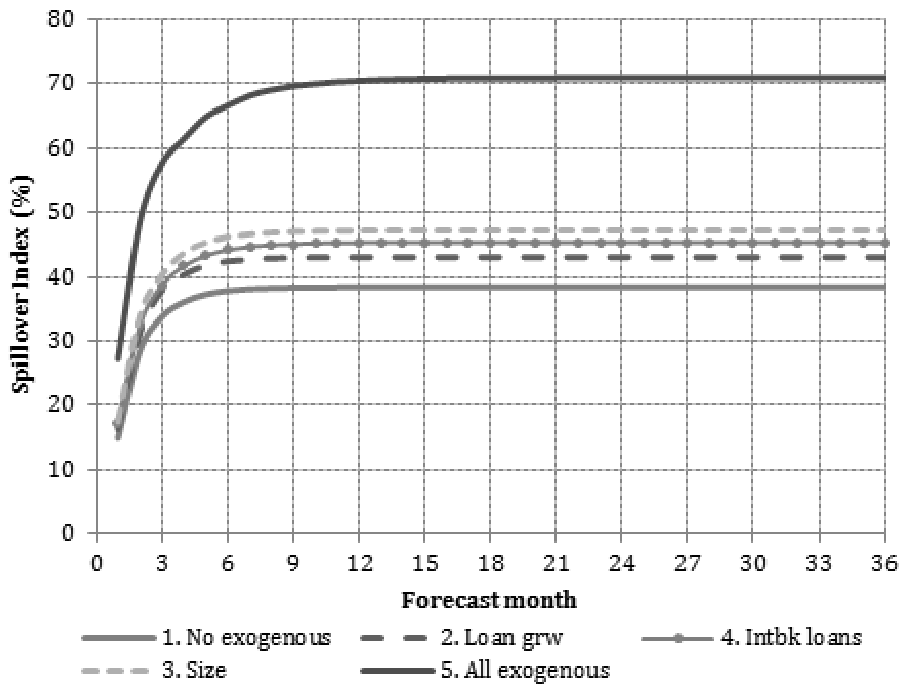
Note: Each panel presents the composition of the Spillover Index for a forecast period of 36 months ahead. The variance decomposition uses a monthly VAR specification of order 2 defined using AIC. The Cholesky factorization is conditional to the length considered in the panel. Each cell (i, j) shows the contribution to the variance of the $k - months$ ahead NPL ratio forecast error value of bank i coming from innovations of the NPL ratio of bank j. The bottom right corner of each panel contains the overall spillover index for each forecasted horizon.

c. Spillover Index and Forecast Horizons

We now analyze how the spillover changes if we use different forecast periods. Figure 4 plots the values of the spillover index for the 5 model specifications and for 1 to 36 forecast horizons. This figure also allows us to see how the level of the spillover increases as we include exogenous variables. The lower line corresponds to the values of the spillover index for the specification without any control variable and for all time horizons, while the line in the top of the figure represents the model with all control variables.

Figure 4 shows that the spillover index increases as we expand the number of forecasted periods. We can also observe that the value of the spillover index follows an asymptotic shape; it increases very quickly from the 1 to 6 month horizons and then gradually attains its long-term value. We interpret this result as evidence that in the long run the level of contagion or spillover in the system plays a more relevant role compared to the short-term. Considering for example the model with all exogenous variables (top line in Figure 4), the spillover effect accounts for only 30 percent of the risk in the system using 1 forecast period, but it explains more than 70 percent of the credit risk using 12 or more forecast periods. Our findings support the idea that in the long run a greater proportion of the variation of the NPL ratio for each institution will depend on the risk variation in the whole system. This finding is in line with common wisdom that in the long run, the most relevant risk is the systemic risk.

Figure 4. Evolution of Spillover Index using Monthly Changes in Banks' NPL Ratio as Proxy for Credit Risk.

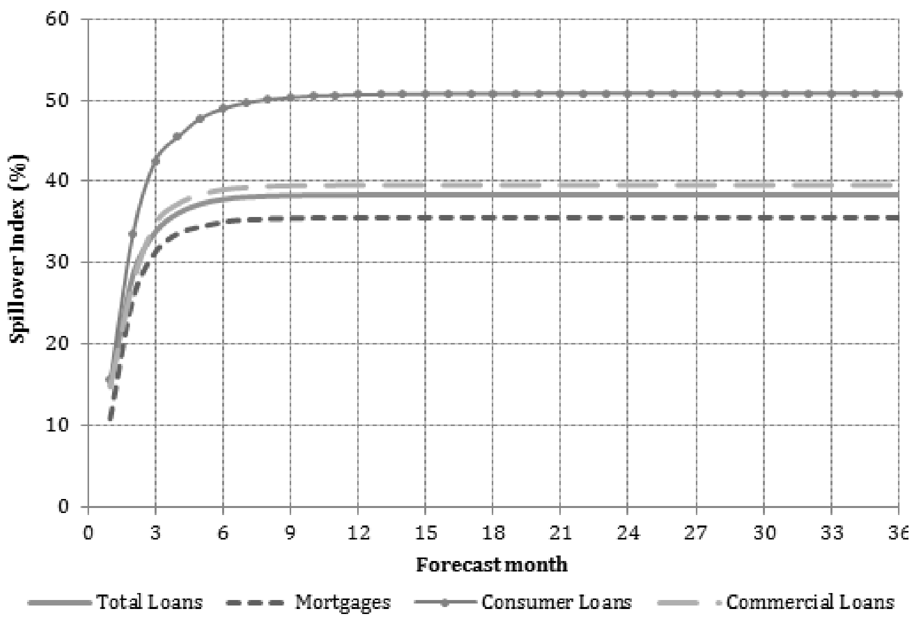


Model 1 does not include exogenous variables; model 2 uses loan growth ratio, model 3 controls for size measured as the log of total assets, model 4 considers the percentage of interbank loans to total loans, and the fifth model includes all three exogenous variables. The variance decomposition uses a monthly VAR of order 2. Lag-order is defined using AIC. Forecast periods are from 1 to 36 months.

d. Spillover Index by Type of Credit

We now turn to analyze differences between the spillover processes for the three types of credit. Table 3 presents the spillover index for each type of credit with a forecast of 36 months ahead. These results are the analogous to the ones presented in Table 2, Panel A and there are no exogenous variables in the models. Compared to total loans, mortgages is the only type of credit that present a lower level of spillover index, while consumer loans has the highest value. In order to compare the diffusion process of risk between credit portfolios over several forecasted horizons, figure 5 graphically presents the values of the spillover indexes for forecasting periods from 1 to 36 month by each type of credit. Consistent with the results above, we observe that in all cases the spillover index increases monotonically and is positively related with the number of periods forecasted ahead. Also the indexes increase rapidly from 1 to 6 forecast periods and then all of them stabilize. Once again the contribution of individual risk is important over the short run but becomes less relevant in the long run relative to the overall spillover effect.

Figure 5. Evolution of the Spillover Index by Type of Credit using Monthly Changes in Banks' NPL Ratio as Proxy for Credit Risk.



The variance decomposition uses a monthly VAR of order 2. Lag-order is defined using AIC. Forecast periods are from 1 to 36 months.

Regarding the differences between types of loans, mortgages present the lowest long-run spillover index among all other portfolios, around 35 percent in 36 forecast periods, compared to consumer loans that present a spillover of 50 percent in the same forecast horizon. Apparently riskier types of credit, such as consumer loans, are more exposed to exogenous sources of risk. Comparing the spillover effects of consumer loans to mortgage and commercial loans, it is possible that differences between intrinsic features like covenants and guaranties, not required for consumer loans, allow institutions to be more immune to contagion from other banks.

Table 3. NPL Ratios Spillover Index, by Type of Credit (36 Forecast Periods) as Proxy for Credit Risk.

Panel A. Commercial loans	Afirme	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Invex	Ixe	Mifel	Monex	Stander	Scotia	From Others
Afirme	73.40	1.83	1.46	1.05	1.76	0.93	3.12	2.58	4.18	0.87	3.20	2.22	0.04	0.63	1.00	0.24	1.50	26.6
Azteca	2.78	74.91	4.89	0.92	2.66	2.44	1.91	0.38	0.56	0.63	3.41	0.57	0.67	0.25	1.47	0.58	0.94	25.1
Bajio	2.78	3.31	68.82	0.74	2.91	0.66	0.88	0.89	0.53	2.76	4.15	0.42	2.74	3.49	1.30	0.46	3.16	31.2
Bnamex	1.63	2.13	1.53	68.40	2.43	0.46	6.50	1.34	6.99	0.90	0.59	2.22	0.35	1.30	1.82	0.15	1.26	31.6
Bregio	3.46	0.54	4.64	0.70	58.24	3.73	0.33	2.05	2.70	0.97	4.42	0.94	8.58	2.58	1.26	3.25	1.61	41.8
Bansi	3.95	1.53	1.42	1.91	0.63	73.60	2.77	1.60	0.79	0.33	0.75	0.73	0.95	6.93	1.28	0.24	0.59	26.4
BBVA	7.33	1.61	1.78	3.69	3.44	1.55	58.51	1.40	5.04	2.37	2.58	2.12	1.69	2.57	1.22	1.42	1.67	41.5
Banorte	9.06	0.73	3.19	4.34	3.68	3.41	5.66	54.27	2.98	1.92	1.60	0.90	2.27	1.85	0.77	2.74	0.62	45.7
HSBC	0.42	3.37	0.66	7.58	2.40	2.22	1.00	1.93	60.69	0.30	1.93	6.71	3.45	0.07	2.22	0.14	4.91	39.3
Inbursa	2.28	7.68	1.51	3.94	3.38	2.07	0.37	3.62	5.90	58.12	0.98	1.42	1.01	2.39	3.43	1.61	0.30	41.9
Interacc	1.61	0.40	1.47	4.34	5.08	11.19	7.77	3.03	3.36	1.37	51.97	1.01	0.39	2.18	1.55	0.61	2.67	48.0
Invex	0.99	3.95	2.80	1.89	6.48	4.38	6.09	4.16	1.36	0.64	3.55	55.87	0.53	0.23	2.93	2.37	1.77	44.1
Ixe	3.00	3.38	3.48	3.19	3.07	11.06	2.38	5.60	2.14	1.89	3.62	4.60	41.84	4.12	2.35	1.18	3.09	58.2
Mifel	0.90	6.30	3.70	1.86	3.14	0.59	3.67	1.42	1.39	3.03	0.44	0.82	4.09	62.12	3.45	1.74	1.33	37.9
Monex	3.56	3.57	0.79	2.70	3.68	2.84	2.12	1.64	7.86	0.34	0.95	4.36	3.26	1.72	57.83	1.55	1.24	42.2
Stander	1.74	2.98	3.50	3.88	8.27	10.42	4.72	2.08	2.18	0.48	3.59	1.64	1.67	2.67	1.49	46.77	1.90	53.2
Scotia	1.62	6.18	0.71	2.00	4.08	1.01	1.03	1.84	3.57	1.92	1.44	3.48	3.21	3.69	1.47	0.86	61.89	38.1
Contrib. to others	47.1	49.5	37.5	44.7	57.1	59.0	50.3	35.6	51.5	20.7	37.2	34.2	34.9	36.7	29.0	19.1	28.6	672.7
Contrib. including own	120.5	124.4	106.3	113.1	115.3	132.6	108.9	89.8	112.2	78.8	89.2	90.0	76.8	98.8	86.8	65.9	90.4	**39.57%**

Panel B. Mortgages	Afirme	Azteca	Bajio	Bnamex	Bregio	BBVA	Banorte	HSBC	Inbursa	Interacc	Ixe	Mifel	Stander	Scotia	From Others
Afirme	62.38	3.61	4.83	1.06	1.01	1.71	0.15	2.46	2.67	2.03	0.84	4.20	0.51	12.55	37.60
Azteca	3.53	80.00	0.44	0.18	0.62	1.14	0.76	2.76	1.29	2.02	3.49	1.63	0.76	1.36	20.00
Bajio	16.62	0.40	45.68	3.66	4.59	2.61	1.00	1.96	4.09	0.88	1.97	12.57	1.36	2.61	54.30
Bnamex	2.32	1.89	0.58	76.98	1.32	0.57	0.41	2.07	2.27	1.70	1.71	3.34	1.13	3.71	23.00
Bregio	13.18	6.96	1.06	1.73	61.46	2.82	0.21	0.99	1.53	1.36	1.39	6.23	0.41	0.67	38.50
BBVA	6.46	5.80	0.49	0.37	2.12	73.78	0.80	1.41	1.15	3.55	0.89	0.52	2.13	0.52	26.20
Banorte	1.25	2.36	1.90	4.15	1.06	4.15	74.64	0.41	2.12	0.42	1.85	4.30	0.52	0.87	25.40
HSBC	6.80	1.44	2.28	2.41	2.10	1.86	0.15	66.67	7.59	0.59	1.77	2.09	3.24	1.01	33.30
Inbursa	1.41	2.84	0.53	2.32	3.68	3.91	0.12	11.11	63.21	2.37	1.91	5.15	0.75	0.70	36.80
Interacc	2.49	1.14	0.93	1.93	4.96	3.27	8.60	1.91	2.88	64.92	0.95	2.65	0.92	2.43	35.10
Ixe	4.12	6.98	2.82	4.17	3.89	4.18	0.38	9.65	5.34	0.67	50.07	2.74	1.16	3.84	49.90
Mifel	19.60	2.56	4.78	1.48	3.20	0.90	0.23	3.59	0.92	0.59	3.44	52.01	5.11	1.57	48.00
Stander	1.41	3.21	4.96	3.22	1.74	5.10	13.26	2.83	2.66	1.42	1.32	2.80	53.45	2.63	46.50
Scotia	1.08	2.11	1.77	2.11	1.20	3.14	0.47	3.80	1.61	1.86	0.71	0.54	2.81	76.79	23.20
Contrib. to others	80.3	41.3	27.4	28.8	31.5	35.3	26.5	44.9	36.1	19.5	22.2	48.8	20.8	34.5	498.0
Contrib. including own	142.6	121.3	73.0	105.8	93.0	109.1	101.2	111.6	99.3	84.4	72.3	100.8	74.3	111.3	**35.57%**

Panel C. Consumer loans	Afirme	Amex	Azteca	Bajio	Bnamex	Bregio	Bansi	BBVA	Banorte	HSBC	Inbursa	Interacc	Ixe	Mifel	Scotia	From Others
Afirme	58.73	2.11	4.12	1.76	1.29	2.61	4.07	1.48	7.18	2.78	7.05	1.14	2.22	1.64	1.82	41.30
American Express	0.78	60.53	4.83	4.25	0.74	7.83	11.30	0.58	0.45	0.35	3.65	1.11	2.04	1.16	0.39	39.50
Azteca	6.98	1.54	69.54	1.96	1.27	2.66	3.43	3.15	1.46	0.98	2.56	0.92	1.08	1.62	0.83	30.50
Bajio	5.46	11.25	5.70	50.47	6.34	1.91	2.77	0.72	0.69	5.72	2.12	0.66	3.37	1.46	1.34	49.50
Bnamex	3.71	1.72	13.29	8.62	44.43	3.25	5.73	0.72	1.66	3.91	4.00	0.49	2.30	2.74	3.42	55.60
Bregio	8.76	17.48	2.95	5.10	3.05	48.09	4.54	0.38	1.80	1.14	2.35	0.98	0.35	0.34	2.70	51.90
Bansi	1.59	5.28	4.04	0.90	2.51	0.63	72.90	2.25	1.76	0.43	2.47	1.55	2.22	1.14	0.34	27.10
BBVA	2.92	1.88	6.04	7.22	1.65	5.55	1.99	59.76	1.05	1.75	2.44	0.50	2.36	2.66	2.22	40.20
Banorte	3.66	11.71	4.38	7.08	2.53	17.44	5.66	1.30	31.44	1.92	1.90	1.15	4.48	2.10	3.26	68.60
HSBC	2.86	21.58	3.58	6.07	4.52	12.92	6.11	4.10	1.98	25.39	2.77	2.77	1.96	1.34	2.05	74.60
Inbursa	4.09	1.93	4.16	2.47	7.06	7.32	2.97	2.52	3.92	12.17	39.78	0.79	3.12	2.92	4.78	60.20
Interacc	0.28	2.99	2.57	2.36	2.82	7.20	4.28	1.89	7.36	1.39	2.49	53.11	6.55	0.50	4.21	46.90
Ixe	1.32	2.87	4.48	0.87	2.46	3.42	5.52	7.32	4.40	2.00	3.72	1.95 5	8.00	0.27	1.40	42.00
Mifel	23.35	9.25	3.26	6.56	4.54	3.96	2.13	0.91	8.53	2.54	4.80	0.45	1.83	27.33	0.54	72.70
Scotia	0.89	15.68	0.94	5.74	1.96	4.42	7.63	1.47	2.01	6.72	4.55	2.21	5.70	2.33	37.75	62.30
Contrib. to others	66.7	107.3	64.3	61.0	42.7	81.1	68.1	28.8	44.2	43.8	46.9	16.7	39.6	22.2	29.3	762.8
Contrib. including own	125.4	167.8	133.9	111.4	87.2	129.2	141.0	88.6	75.7	69.2	86.7	69.8	97.6	49.6	67.0	**50.85%**

Note: Each panel presents the composition of the Spillover Index for a forecast period of 36 months ahead. The variance decomposition uses a monthly VAR specification of order 2 defined using AIC. The Cholesky factorization is conditional to the length considered in the panel. Each cell (i, j) shows the contribution to the variance of the k-months ahead NPL ratio forecast error value of bank i coming from innovations of the NPL ratio of bank j. The bottom right corner of each panel contains the overall spillover index for each forecasted horizon.

6. Conclusions

This paper studies the diffusion process and spillover effects of the NPL ratio among banks operating in the Mexican Banking System. Given the initial level of risk in the system, our approach allows us to observe how innovations in individual institutions affect other institutions and how the process takes place in time. Our research differs from those described in the previous literature in several dimensions. First, we proceed in a manner closer to Furfine (2003) and focus on explaining the system from a within perspective instead of examining from exogenous macro factors that may affect the system. In this line, we analyze the long-run risk of the system and the contributions to risk of the elements in the system, instead of using the short-run positions of the banks. Second, we propose a method to measure the overall size of risk due to innovations in each bank and we are able to evaluate the size of the risk for different specifications and over several forecast horizons. Third we identify both the contributions of the individual banks to the aggregate and the risk of other banks, and we construct a measure of the overall importance of spillover effects on the system. Finally, our method allows us to compare the relevance of the spillover as we increase the time span of the forecasted period.

We extend the Diebold and Yilmaz (2009) methodology to identify the long-run diffusion process and build a spillover index of the effect that the credit risk of each bank has on the rest of the banks in the system. The method models the NPL ratio by assessing the contribution of each bank's ratio to the system. We also prove that the level of spillover is not constant over time but rather that it increases gradually reaching a long-term equilibrium level. Indeed, our findings suggest that the diffusion process takes time to spread over the whole system; in the short run (one to six months), credit risk is mainly due to the institution intrinsic characteristics, but in the long-run, approximately 70 percent of the credit risk is attributable to systemic risk. In any case, the spillover index is always important but never the unique determinant of the long-run risk in a banking system. In additional models we control for the size of the institution, loan growth rates and interbank activities trying to capture sources of risk. The results demonstrate that the level of risk in the system decreases when exogenous variables are considered, implying that those variables are able to capture individual risk. However, given the lower level of risk attributed to the whole system, the spillover effect becomes more relevant.

Finally, we analyze the diffusion and contribution of risk between different types of credit within a closed banking system. Particularly, we find that the spillover effect is more relevant for riskier credit portfolios compared to portfolios with real guaranties.

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