Spillovers and Long-Run Diffusion of Non-Performing Loans Risk[1]

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Abstract

This paper analyzes the diffusion and spillover effects of credit risk among banks within a banking system, using the Mexican financial system as a case study. Credit risk is measured by the non-performing loans ratio (NPL). Our method builds on work by Diebold and Yilmaz (2009) to decompose spillovers observed among banks' portfolio risk. 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 among 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 2000 and 2010 suggest that the overall spillover effect index accounts for 60 to 75 percent of the observed variation and that the longer the time period we consider, the stronger this spillover effect is. Moreover, contrary to the common view, the spillover effect realized through the diffusion of risk is bidirectional between small and large banks, rather than only one type affecting the other.

Key Words: *Non-performing loans, credit risk, spillovers, systemic risk.*

Subject Areas: *C58 - Financial Econometrics, G21 - Banks, G32 - Financial Risk and Risk Management.*

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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 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.

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.[2] For instance, 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 model the banking NPL ratio by analyzing the degree of spillover over time between the NPL ratios from several banks within a single banking system. In particular, we seek to go beyond the explanation of a macroeconomic environment causing debtors to miss payments to determine the extent to which the NPL ratio of one institution is determined by the

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

NPL ratios of other institutions. Furthermore, we do not only assess the interdependence of NPL ratios but also explain how this external influence on credit quality evolves over time. In other words, our approach makes it possible to establish when the intrinsic risk stops being relevant and banks are only exposed to the systemic risk. To perform our study, we use data about non-performing loans ratios for three types of loan portfolios (commercial, consumer and mortgages) from 14 Mexican banks that operated uninterruptedly over the past decade (2000 – 2010). The banks in the sample consistently represent more than 90% of the total assets of the system and more than 95% of total loans.

The degree of influence of other banks' credit quality is measured using the spillover index method proposed by Diebold and Yilmaz (2009), which is based on the error in forecast variance decomposition and estimated with a vector autoregressive (VAR) equilibrium process. With this method, they assessed the degree of connection between returns and the volatility of different equity markets around the world, providing an intuitive measure for this interdependence.

We adapt this method to identify the long-run equilibrium of credit risk interdependence between banking institutions and to determine how important this effect becomes as we increase the timeframe of prediction. The main advantage of this method is that it reports the percentage of forecast error variance from one entity that can be attributed to other entities, i.e., the diffusion effect on the NPL ratio. The spillover index also allows us to observe the magnitude of the diffusion effect on the NPL ratio for different time horizons in the system.

Our study contributes to the literature in two 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, we add to the original method by using not just one forecast period but progressively increasing the length of the prediction horizon to study the relative importance of diffusion on each entity over time. As the forecast horizon is expanded, it becomes possible to describe how the diffusion process takes place and how the systemic risk becomes relevant over time as measured by the spillover index.

According to our results, the spillover effect between banks in the long run accounts for approximately 70% of a bank's NPL ratio variance over a forecast period of 5 years for the whole portfolio and for each type of loan. This finding indicates that the level of the NPL ratio in the long run is mostly attributed to systemic risk and that only 30% is the result of the intrinsic risk in each bank. The progressive increase of the forecast window (from 1 to 60 months) shows that the diffusion process is increasing up to certain long-run equilibrium level. Considering a one-month forecast horizon, there barely is any spillover (between 9 and 13% depending on the type of credit). However, the index rises to 40% in 6 months and almost 60% in 12 months. The diffusion process reaches long-run equilibrium in approximately 18 months. In sum, the spillover effect explains a larger percentage of the aggregate risk as we increase the forecast period. All results are qualitatively robust to the reordering of input variables, as the purpose is not to assess the causality of risk diffusion between banks but rather to measure the level of spillover.

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 during the 2000-2010 decade. 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 with problem loans finding that low levels of cost efficiency Granger-cause increases in non-performing loans; the premise is that cost-inefficient managers are also poor loan managers. Espinoza and Prasad (2010) is a good example of recent non-performing loans modeling. They use a sample of banks in the Gulf Cooperative Council and the dependent variable is the logit transformation of the NPL ratio. Their results show that both macro factors and bank-specific characteristics influence the level of NPLs when controlling for size, efficiency, credit growth, capital adequacy, and lag interest rate margin. 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 were relevant in determining NPLs. 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. Furthermore, they highlight that the explanatory power of significant variables changes over time, and they detect a structural break in the data. Finally, Tabak, Fazio and Cajueiro (2011) explore the relation between loan portfolio concentration and a bank´s risk and return in Brazil. The variable used to proxy risk is the logarithm of a bank's NPLs. They prove that loan portfolio concentration increases returns and reduces default risk. Moreover, they show 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.[3]

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. They investigate transmission channels globally and regionally using 80 currency crisis episodes from 20 countries in Europe, Asia and Latin America. According to them, the probability of contagion is higher at regional levels than at the global level because the ability to predict a domestic crisis when a crisis occurs somewhere else depends highly on location. Their main finding is that some of the contagion attributed to trade can be related to linkages in the financial sector, principally common bank lenders. This transmission channel is more powerful when several countries suffer a period of crisis within the same region.

In studies with some different approaches, contagion has proven to be relevant in assessing bank fragility. Gonzalez-Hermosillo, Pazarbaşioğlu and Billings (1997) conclude that in Mexico, the contagion effects, defined by interbank activities such as deposit loans, might play a role in both the likelihood and timing of failure, as they tend to rapidly increase before crisis periods. The authors identify the factors behind financial fragility and classify them into two determinant parts: those contributing to the likelihood of failure and those determining the timing of failure in a system. In their exercise, they find that a higher percentage of NPLs in a portfolio increases the fragility of the banks in a system (as defined by the probability of failure) after some threshold level, while the macro exposure of the system is determined by the banks' growth in lending.

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

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. Furfine selects the second type of method to analyze the interbank relative exposures in the US banking system in February-March 1998. He quantifies the potential contagion effect from one bank to the other, finding 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 risk diffusion model builds 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 diffusion of risk among agents, banks in our case, in a closed system. Moreover, it is possible to calculate a spillover index 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 the long-run aggregate credit risk of the banking system can be represented in terms of the individual NPL ratios of the banks in the economy. 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:

$$\boldsymbol{X}_t = \boldsymbol{\Phi}(L)\boldsymbol{\varepsilon}_t \qquad (1)$$

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 $\boldsymbol{\varepsilon_t}$ in the model is the "shocks" or "innovations".

The $\boldsymbol{\Phi}(L)$ vector is recovered using ML-VAR estimation, and with this set of parameters, we represent the model in terms of the normalized moving average representation as:

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

where $\mathbf{A}(L) = \boldsymbol{\Phi}(L)Q_t^{-1}$, $\boldsymbol{u}_\mathbf{t} = Q_t\ \boldsymbol{\varepsilon}_t$, $E(\boldsymbol{u}_t\boldsymbol{u}'_t)=I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of $\boldsymbol{\varepsilon_t}$.

Now, it is possible to 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. This prediction, using information up to t, is defined by ${}_t\boldsymbol{X}_{t+k}$ in terms of the following equation:

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

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

$$ \boldsymbol{e}_{t+k} = \boldsymbol{X}_{t+k} - {}_{t}\boldsymbol{X}_{t+k} \tag{4} $$

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

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

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

$$ \boldsymbol{e}_{t+k} = \boldsymbol{X}_{t+k} - {}_{t}\boldsymbol{X}_{t+k} = \quad \boldsymbol{A}(L)_{t+k}u_{t} \tag{6} $$

where:

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

With these elements at hand, the variances of forecast error for the risk for each of the banks allow us to identify and calculate the variance decomposition into parts attributable to the various VAR system shocks.

Based on the error in forecast variance decomposition, the method permits the identification of two types of diffusion elements: first, the fraction of the *k-periods-ahead* variance in the error in forecasting the risk of a bank *j* that is due to the bank's own shocks; and second, the amount of this variance of error for bank *j* that is due to the indirect transmission of shocks from other banks. These two potential contribution factors are what we define as the diffusion process of risk among banks.

As in Diebold and Yilmaz (2009), we construct and define the *own variance shares* and *cross variance shares (or diffusion)* to be the fractions of the *k-step* ahead error variance in forecasting each bank's risk due to its own shocks and due to other risks, respectively.

To illustrate our above description, let us consider the k-periods forward Cholesky matrix of J banks in the VAR system to be:

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

where $\boldsymbol{e}_{t+k} = \boldsymbol{A}(L)_{t+k}\boldsymbol{u_t}$ as defined by equation (6).

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

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

The decomposition of the error in variance allows us to identify the diffusion, which then permits the calculation of Jx(J – 1) possible spillover effects to consider. That is, it requires the calculation of the effects 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 $\boldsymbol{A}(L)_{t+k}$ 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:

$$ {}_kS = \frac{\sum_{k=0}^{K-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{J} [a(L)^2_{i,j}]_{t+k}}{\sum_{k=0}^{K-1} Trace(\boldsymbol{A}(L)_{t+k} \boldsymbol{A}(L)_{t+k}')} \times 100 \qquad (10) $$

The index ${}_kS$ 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 periods of forward forecasting *k* to identify the relative importance of diffusion of risk as we increase the length of prediction of any bank NPL ratio.

4. The Mexican Banking System (2000 – 2010) 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;[4] by 2005, the midpoint of the decade, 83% of bank assets and 82% of deposits were controlled by foreign institutions. With new international players, the credit granting business was fully restored, and the writing-off process of past-due loans derived from the crisis of the 1990s was concluded because the new owners wanted to clean their balance sheets.

There are two clearly defined periods within the decade: the first between 2000 and 2005 when the credit market concluded its contraction process as the newly issued credit did not offset

[4] 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.

the loans that were being written off, and a second period from 2006 to 2010 where the credit growth rates became positive and high, slowing down only during the economic turmoil in 2008-2009. The evolution of credit balances during this period is shown in Figure 1. Notably, the value of the consumer portfolio increased by more than 10 times, while the mortgage and commercial loans portfolios doubled and tripled their values, respectively.

As the structure of the banking system did not suffer any other structural break during the 2000s, the period of study for the NPL ratio diffusion process is between December 2000 and December 2010. The data consist of a panel with end-of-the-month balances of credit portfolios for the 14 largest banks in Mexico with 121 monthly observations. 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 14 banks represented the 98.6% of the total credit market in Mexico in December 2000, and as of December 2010, they represent the 93% of the market. Figure 2 presents the evolution of the NPL ratio for the Mexican Banking System over the studied period. After December 2001there is a sharp decline in the ratio, which is mainly induced by an aggressive writing-off process of past due loans that 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.

5. Estimation and Results

The estimation of the spillover index between banks is performed for each type of credit and uses several forecast horizons to assess how the diffusion process takes place over time. We first present detailed results, in which it is possible to review the decomposition of the index among banks and to measure their contributions to the NPL ratio of other institutions. After that, we present how the spillover index evolves when the forecasted horizon is expanded. Compared to Diebold & Yilmaz, 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 2000) and progressively change the forecast period from 1 to 60 months. This method allows us to determine how long it takes for the credit risk to spread throughout the whole system and how the relevance of the diffusion process increases over time.

For the first analysis, Table 2 through Table **5** present results for three forecasted estimation windows (1, 12 and 60 months) for each type of loan portfolio and the total loan portfolio. The results are presented 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 selected forecasted window and for the corresponding loan portfolio. For example, it can be seen in Panel B from Table 2 that the spillover index for all loans over a 12 month forecast horizon is 60.13 percent. This table also provides an "input-output" decomposition of the spillover index.

However, in our case, it is not possible to derive conclusions about the causal relations of the shocks between institutions. The key insight from these tables is that in every case, and in the long run, approximately 70 percent of the forecast error variance comes from spillovers.

If we consider the individual contributions of each back to its own NPL ratio (the diagonal values), then over a one month horizon, the error variance is almost fully attributable to the institution itself (Panel A in Tables 2 to 5). These results imply that in a very short time forecast horizon, there is very little to no spillover between banks. For example, for the total loans portfolios (Table 2), the bank's own contribution accounts for more than 90 percent of the error variance for the first 7 banks in the sample and for Banregio, while accounting for 70 to 88 percent for the rest of the sample. It is worth noticing that in all tables, the forecast error variance for BBVA-Bancomer depends only on its own shocks (a 100 percent value). However, recall that by construction of VAR estimations, these values are the result of the order in which the series are supplied to the model. For this reason, the appearance of BBVA-Bancomer with an "own contribution" of 100 percent for all portfolios is an artifact of the construction of the model.[5]

The diagonal values dramatically decrease in almost every case when the forecasted horizon is extended to 12 and 60 months (Panels B and C), indicating that a bank's own innovations become less important relative to innovations in other institutions. There are several cases where the contributions from other banks are 90 percent of the forecast error variance, such as Bajio and Amex in consumer loan portfolios (Panel C, Table 4) or HSBC, Banregio and Afirme in the mortgage loans portfolios (Panel C, Table 5). In sum, for a 60 month horizon, the results show that more than 50 percent of the forecast error variance of the NPL ratio in *bank i*

[5] For the sake of robustness, we estimated the system using several randomly selected series order. In every case, the forecasted error variance coming from the institution itself was 100 percent for the first bank in the sample, although the magnitude of the overall spillover index remained almost unchanged.

depends on shocks to the NPL ratio of other institutions. This dependence is the case for almost every bank and for every type of credit.

We now turn to analyze differences between the spillover processes for the three types of credit portfolios. Although the spillover indexes for the three portfolios and for the total loan portfolio are above 65 percent in the long run, there are some differences worth mentioning. For instance, the highest spillover occurs in the consumer loans portfolio (75 percent), despite the fact that in the short run, it has slightly smaller spillover than other portfolios. Commercial loan portfolios present the lowest long-run spillover index among all other portfolios (67 percent). These results suggest that in longer time horizons, consumer loans are more sensitive to risk diffusion among banks.

We also observe the processes do not occur with the same velocity. For instance, as we increase the forecasted horizon, the spillover index of mortgage loans rises at a slower pace than the index for commercial loans, even though mortgage loan portfolios present a higher spillover index in the long run (71 vs. 67 percent). This finding implies that the diffusion process of credit risk is slower than the diffusion process in the mortgage market.

Another finding derived from Tables 2 to 5 is that contrary to the common view, the spillover effect through the diffusion of risk is bidirectional. The spillover effect goes from small to large banks and vice versa. For instance, Afirme, Mifel and Bansi, the three smallest banks in the sample, have diffusion effects on large banks such as BBVA-Bancomer and Banamex, but these effects are only relevant when we increase the forecasted horizon.

Figure 3 graphically presents the values of the spillover indexes for forecasting periods from 1 to 60 month by each type of credit in order to compare the diffusion process of risk between credit portfolios over several forecasted horizons. Consistent with the results above, it can be seen that the spillover index increases monotonically and is positively related with the number of periods forecasted ahead. The index follows an asymptotic shape; it increases very quickly from the 1 to 6 month horizons and then gradually attains its long-term value. Previous results indicate that the contribution of individual risk is important over the short run but becomes insignificant in the long run relative to the overall spillover effect. In the long run, 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. Furthermore, the spillover effect for any *k-periods* ahead forecast, as measured by the spillover index, stabilizes over time around a fixed long-run level; the intuition behind this result is that the total variation in bank risk due to systemic risk reaches an equilibrium level of approximately 75 percent for every institution.

6. Conclusions

This paper studies the diffusion process and spillover effects of the NPL ratio among banks operating in the Mexican Banking System. Our approach 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 the outside the macro factors that affect the system. Nonetheless, we analyze the long-run risk of the system and the contributions of the elements, instead of using the short-run positions of the banks. Second, we are not only able to identify both the contributions of the individual banks to the aggregate and the risk of other banks but are also able to 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 until it gradually reaches 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 caused by the institution itself, 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. Furthermore, our results suggest that, contrary to common belief, the diffusion of risk between banks, as measured by the NPL ratio, is bidirectional: spillover from small banks affects large banks, and vice-versa.

The application of our methodology can be extended to include the diffusion and contribution of risk between different types of credit within a closed banking system. For instance, the method could be used to measure the contribution within and between a bank's numerous portfolios and then to identify which of the elements within a credit portfolio is more dominant in diffusing risk to other credit elements. With this spillover measure, policy makers could develop signal warnings using those types of credit that have a higher impact on the rest of the bank's portfolio.

References

Barr, R., Seiford, L., and Siems, T., 1994. Forecasting Banking Failure: A Non-Parametric Frontier Estimation Approach, Recherches Economiques de Louvain, 60, 411-429

Berger, A., and DeYoung, R., 1997. Problem Loans and Cost Efficiency in Commercial Banks. Journal of Banking and Finance, 21, 849-870.

Bernstein, D., 1996. Asset Quality and Scale Economies in Banking. Journal of economics and Business, 48, 157-166.

Brock, P. and Rojas-Suarez, L. 2000. Understanding the Behavior of Bank Spreads in Latin America. Journal of Development Economics, 63, 113-34.

Demirgüç-Kunt, A. and Detriagache, E., 1998. The Determinants of Banking Crises in Developing and Developed Countries. IMF staff papers, 45, 81-109.

Diebold F.X., and Yilmaz K., 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. The Economic Journal, 119, 158-171.

Dungey, M., Fry, R., González-Hermosillo, B., and Martin, V., 2005. Empirical modelling of contagion: a review of methodologies. Quantitative Finance, 5, 1, 9-24.

Eichengreen, B., Rose, A., and Wyplosz, C., 1996. Contagious Currency Crisis. National Bureau of Economic Research Working Paper. Vol. 5681.

Espinoza, R., and Prasad, A., 2010. Nonperforming Loans in the GCC Banking System and their Macroeconomic Effects. IMF working paper, WP/10/224, October.

Festic, M., Kavkler, A., and Repina, S., 2011. The Macroeconomic Sources of Systemic Risk in the Banking Sectors of five new EU Member States. Journal of Banking and Finance, 35, 310-322.

Furfine, C. H., 2003. Interbank Exposures: Quantifying the Risk of Contagion. Journal of Money Credit and Banking, 35, 111-128.

Goldstein, M., Kaminsky, G. L. and Reinhart, C., 2000. Assesing Financial Vulnerability, ans Early Warning System for Emerging Markets. Institute for International Economics, Washington, D.C., June.

Gonzalez Hermosillo, B., 1999. Determinants of ex-ante banking system distress: A micro-micro empirical exploration of some recent episodes. IMF working paper, WP/99/33, March.

Gonzalez Hermosillo, B., Pazarbasioglu, C. and Billings, R., 1997. Determinants of banking system fragility: A case study of Mexico. IMF Staff papers, Vol. 44, No. 3, September.

Kaminsky, G. L., and Reinhart, C. M., (2000). On crisis contagion, and confusion. Journal of International Economics, 51, 145-168.

Meeker, L.G. and Gray, L., 1987. A note on Non-Performing Loans as an indicator of asset quality. Journal of Banking and Finance, 11, 161-168.

Reinhart, C., and Rogoff, K. S., 2009. This time is different. Princeton University Press. Princeton, NJ.

Tabak, B. M., Fazio, D. M., Cajueiro, D. O., The effects of loan portfolio concentration on Brazilian banks' return and risk. Journal of Banking and Finance. Doi:10.1016/j.jbankfin.2011.04.006

Appendix

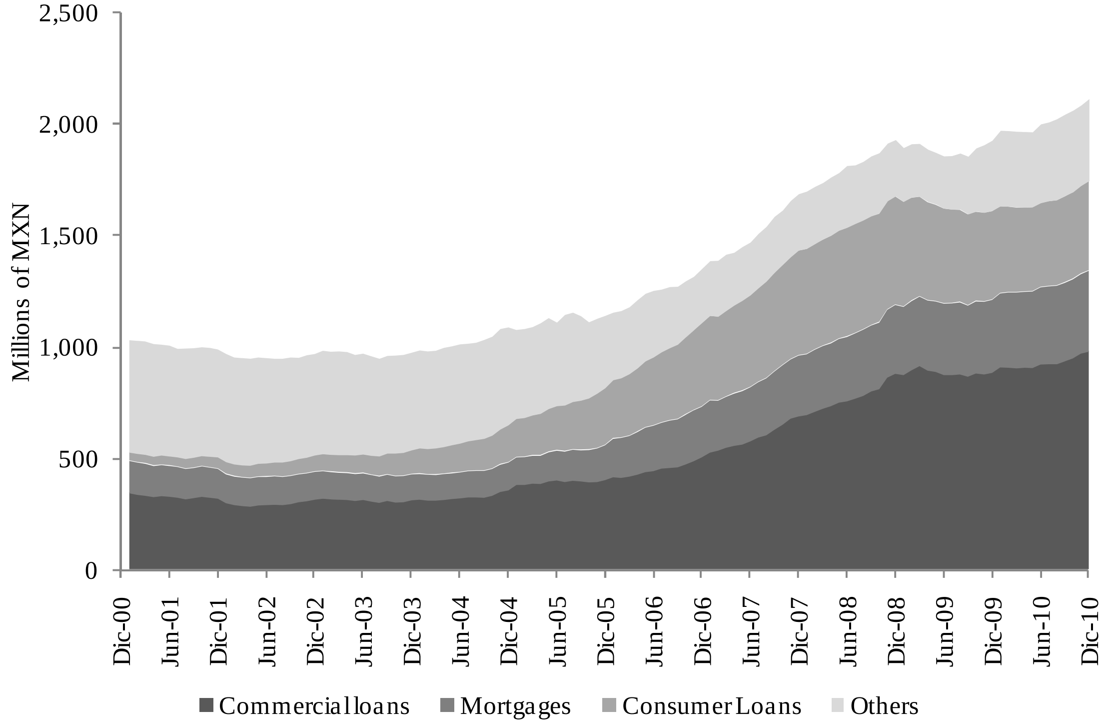

Figure 1: Evolution of monthly total balance by type of credit. *Source*: National Banking and Securities Commission

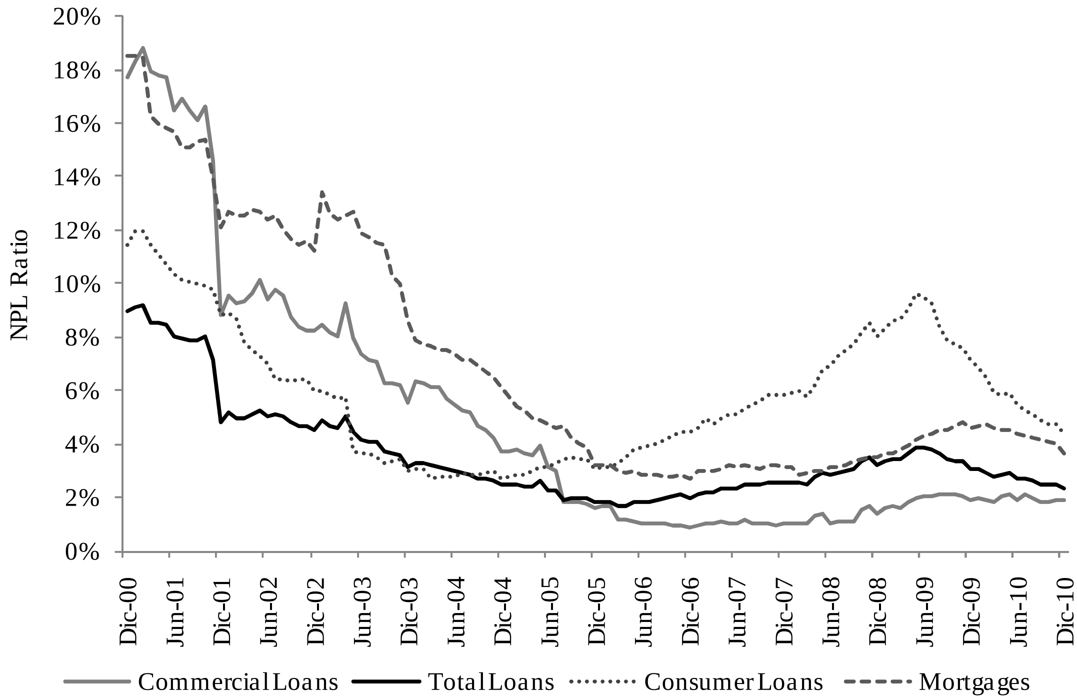

Figure 2: NPL Ratio dynamics by type of credit and for total loans. *Source*: National Banking and Securities Commission

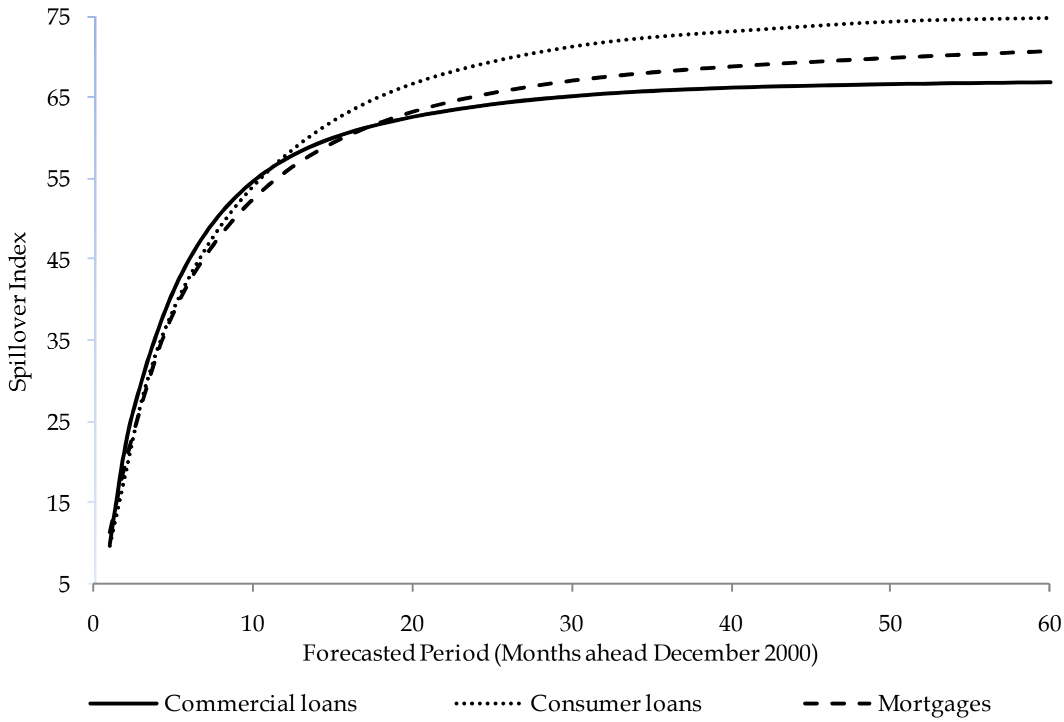

Figure 3: Evolution of spillover index by type of credit. *Source*: National Banking and Securities Commission

Table 1:
Sample statistics, NPL Ratio for total loans and by type of credit, monthly data, 2000:12 – 2010:12

	Mean	T-Stat	St. Dev.	Skew	Kurtosis		Mean	T-Stat	St. Dev.	Skew	Kurtosis
Total loans portfolio						*Commercial loans portfolio*					
BBVA	3.37%	23.55	1.57%	0.898	0.237	BBVA	3.40%	9.93	3.77%	1.526	1.618
Banamex	3.91%	25.55	1.68%	0.328	-1.268	Banamex	6.11%	10.42	6.44%	0.535	-1.333
Santander	1.36%	20.58	0.73%	1.447	1.368	Santander	1.42%	12.55	1.25%	2.320	6.473
HSBC	5.71%	20.10	3.13%	0.813	-0.921	HSBC	10.54%	12.01	9.65%	0.674	-1.325
Banorte	4.07%	7.49	5.97%	2.731	5.762	Banorte	8.65%	5.71	16.66%	2.609	5.186
Scotia	4.85%	15.87	3.36%	1.512	1.028	Scotia	6.10%	8.98	7.47%	1.871	2.295
Inbursa	1.60%	21.07	0.84%	0.410	-0.433	Inbursa	1.60%	18.86	0.93%	0.588	-0.452
Bajio	2.04%	20.09	1.12%	0.415	-0.684	Bajio	1.82%	19.88	1.01%	1.072	1.031
IXE	2.11%	7.92	2.94%	2.289	4.713	IXE	2.80%	5.66	5.44%	3.361	12.556
Banregio	1.67%	30.99	0.59%	0.439	-1.155	Banregio	1.49%	25.94	0.63%	0.694	-0.425
Afirme	1.88%	13.10	1.58%	1.233	0.303	Afirme	2.25%	16.00	1.55%	0.910	-0.259
Amex	4.49%	17.48	2.83%	0.944	-0.624	Amex	NA	NA	NA	NA	NA
Mifel	2.22%	26.13	0.94%	1.401	3.466	Mifel	2.84%	25.59	1.22%	0.826	1.164
Bansi	2.30%	26.13	0.97%	0.926	0.754	Bansi	2.61%	30.70	0.93%	0.896	0.884
Consumer loans portfolio						*Mortgage portfolio*					
BBVA	5.31%	34.63	1.69%	0.473	-0.154	BBVA	7.04%	17.21	4.51%	0.590	-1.301
Banamex	5.03%	25.66	2.16%	0.496	-1.071	Banamex	4.16%	29.48	1.55%	0.545	-1.005
Santander	3.71%	19.78	2.06%	1.464	1.336	Santander	2.89%	20.31	1.57%	0.960	-0.423
HSBC	9.76%	15.84	6.77%	0.743	-0.757	HSBC	10.90%	20.11	5.96%	0.781	-1.114
Banorte	7.32%	10.50	7.67%	3.109	10.206	Banorte	8.69%	7.80	12.24%	2.397	4.949
Scotia	3.38%	16.15	2.30%	0.347	-1.075	Scotia	10.97%	12.49	9.66%	0.996	-0.685
Inbursa	2.92%	13.91	2.31%	0.103	-1.259	Inbursa	6.58%	17.87	4.05%	-0.276	-1.343
Bajio	3.21%	16.53	2.13%	-0.390	-1.093	Bajio	5.52%	12.91	4.70%	0.193	-1.076
IXE	3.25%	24.24	1.48%	1.798	5.795	IXE	3.19%	9.71	3.62%	2.457	5.506
Banregio	3.54%	17.39	2.24%	-0.231	-1.088	Banregio	1.21%	7.55	1.76%	1.528	1.058
Afirme	6.76%	35.25	2.11%	0.219	-0.079	Afirme	2.53%	8.91	3.12%	1.519	1.433
Amex	4.52%	17.71	2.81%	0.952	-0.611	Amex	NA	NA	NA	NA	NA
Mifel	2.45%	5.74	4.69%	1.884	2.302	Mifel	1.71%	6.23	3.02%	1.859	2.375
Bansi	5.20%	13.58	4.21%	1.123	2.311	Bansi	NA	NA	NA	NA	NA

Source: National Banking and Securities Commission
Note: the table presents statistics for the monthly NPL ratio for each bank from December 2000 to December 2010. NPL ratio divides the NPL balance relative to total loans. The t-statistic tests for the null hypothesis that mean NPL ratio is cero.

Table 2: Spillover Index, NPL ratio / Total Loan Portfolio

	From														
To	BBVA	Bnmex	Std	HSBC	Bnte	Scotia	Inbrs	Bajio	IXE	Bregio	Afirme	Amex	Mifel	Bansi	Contribution From Others
Panel A: 1 month															
BBVA	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Banamex	0.1	99.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Santander	3.4	3.5	93.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.0
HSBC	1.9	0.4	0.4	97.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.7
Banorte	5.8	0.0	1.7	1.7	90.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.3
Scotia	2.6	0.0	0.3	0.6	0.5	96.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0
Inbursa	5.8	0.0	2.8	0.0	0.0	0.2	91.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.9
Bajio	2.8	0.0	0.6	0.1	12.0	0.1	7.1	77.4	0.0	0.0	0.0	0.0	0.0	0.0	22.6
IXE	1.6	0.0	1.8	0.0	3.6	4.6	0.1	0.0	88.2	0.0	0.0	0.0	0.0	0.0	11.8
Banregio	0.5	0.3	1.7	0.1	0.4	0.9	2.3	0.4	0.0	93.5	0.0	0.0	0.0	0.0	6.5
Afirme	0.0	6.1	0.9	0.0	0.0	0.9	0.3	2.0	0.1	3.5	86.3	0.0	0.0	0.0	13.7
Amex	1.0	0.9	6.0	0.2	0.9	3.0	1.8	0.6	0.4	0.3	2.3	82.8	0.0	0.0	17.2
Mifel	1.5	0.6	1.8	0.2	4.5	0.1	0.5	1.9	0.2	1.2	0.2	0.4	87.0	0.0	13.0
Bansi	0.4	3.8	1.9	7.8	11.5	1.4	0.3	0.0	0.5	0.0	0.3	1.0	1.1	70.1	29.9
Contribution to others	27.4	15.7	19.8	10.6	33.4	11.1	12.4	4.8	1.1	5.0	2.8	1.3	1.1	0.0	146.5
Contrib. includ. own	127.4	115.6	112.8	107.9	124.1	107.1	103.6	82.3	89.3	98.4	89.1	84.1	88.1	70.1	**10.47%**
Panel B: 12 months															
BBVA	20.2	4.3	8.8	27.5	0.4	5.9	4.0	0.2	6.8	9.4	3.9	1.1	4.7	2.9	79.8
Banamex	3.9	63.0	0.7	1.2	1.5	2.9	1.1	0.8	1.6	5.0	3.3	5.2	7.1	2.7	37.0
Santander	0.7	2.3	66.0	0.8	2.4	0.1	3.6	0.3	0.3	4.8	1.9	16.5	0.4	0.1	34.0
HSBC	0.3	0.3	10.1	50.2	2.4	17.6	2.2	0.2	0.8	7.5	1.5	1.4	1.9	3.8	49.8
Banorte	9.1	0.6	7.3	3.3	35.7	0.5	0.4	1.5	20.1	1.9	3.2	2.1	13.4	0.9	64.3
Scotia	9.1	0.6	9.7	13.9	4.2	30.3	1.7	1.2	18.6	2.1	1.1	1.0	5.5	0.9	69.7
Inbursa	3.6	1.4	15.4	12.7	2.6	3.0	43.1	0.8	1.5	7.7	0.5	1.7	5.3	0.7	56.9
Bajio	4.9	0.2	22.2	4.1	24.9	1.4	4.5	9.8	6.8	3.4	2.1	0.9	14.6	0.3	90.2
IXE	9.7	2.5	11.9	2.8	5.6	4.2	0.7	1.6	39.9	2.5	2.7	3.2	11.6	1.0	60.1
Banregio	1.8	2.5	4.2	6.0	5.3	2.0	8.5	0.7	0.8	40.0	2.3	6.9	18.2	0.8	60.0
Afirme	0.3	11.6	6.9	0.1	2.2	0.3	7.8	3.5	0.8	1.4	51.0	7.8	4.2	2.3	49.0
Amex	1.6	1.2	37.3	5.5	0.3	1.7	11.7	1.2	3.7	5.2	1.0	27.8	1.7	0.1	72.2
Mifel	2.5	0.8	2.4	8.4	10.6	3.6	0.4	1.2	5.2	2.5	4.8	0.6	54.0	3.1	46.0
Bansi	2.7	4.6	14.0	14.4	18.0	7.0	2.4	0.7	2.6	0.3	1.5	3.4	1.1	27.2	72.8
Contribution to others	50.1	32.8	150.8	100.7	80.4	50.2	49.0	13.9	69.5	53.7	29.6	51.9	89.7	19.6	841.9
Contrib. includ. own	70.2	95.8	216.8	150.9	116.1	80.5	92.0	23.7	109.4	93.7	80.6	79.7	143.7	46.8	**60.13%**
Panel C: 60 months															
BBVA	8.4	4.9	23.5	21.4	2.4	7.1	3.0	0.3	3.5	11.5	2.5	0.8	9.4	1.3	91.6
Banamex	3.9	33.0	11.8	2.9	1.4	5.5	5.5	1.3	5.6	3.4	4.5	11.3	7.4	2.5	67.0
Santander	0.9	2.2	61.3	3.3	1.9	2.0	3.3	0.2	1.5	6.9	2.5	12.7	0.7	0.5	38.7
HSBC	2.6	2.7	18.0	32.9	3.8	13.7	1.2	0.6	4.1	8.3	2.5	2.1	5.6	1.8	67.2
Banorte	8.8	2.9	7.7	3.9	31.3	1.0	1.1	1.4	17.6	2.6	4.4	2.0	13.8	1.5	68.7
Scotia	7.9	4.8	16.9	9.5	4.0	15.9	1.3	1.3	14.1	6.3	4.3	0.8	12.1	0.9	84.1
Inbursa	2.8	1.4	24.9	11.5	3.1	3.9	32.2	0.7	1.7	8.2	0.5	2.3	5.9	0.9	67.8
Bajio	3.4	1.1	30.4	3.3	16.4	2.8	6.4	5.5	6.4	4.9	1.9	5.4	11.4	0.7	94.5
IXE	8.8	5.5	14.8	2.2	6.7	3.0	1.6	1.4	28.4	4.8	4.3	2.3	15.2	1.2	71.6
Banregio	2.2	1.5	23.8	12.1	4.8	5.4	6.2	0.5	1.9	22.1	1.3	8.5	8.8	1.0	77.9
Afirme	1.3	4.2	43.9	1.7	1.0	1.4	7.3	1.3	2.7	4.7	11.8	15.7	1.9	1.0	88.2
Amex	1.3	0.6	50.0	5.9	1.1	3.3	7.4	0.6	3.5	7.1	0.6	15.9	1.9	0.8	84.2
Mifel	2.6	1.1	4.9	9.0	11.2	4.2	1.4	1.2	5.5	2.7	4.6	1.7	46.9	3.2	53.1
Bansi	2.5	3.2	21.5	19.0	14.0	11.3	1.9	0.5	2.7	3.0	2.2	3.3	1.7	13.3	86.7
Contribution to others	49.0	36.1	292.0	105.6	71.7	64.3	47.5	11.2	70.9	74.4	36.1	69.0	95.8	17.5	1041.2
Contrib. includ. own	57.4	69.1	353.3	138.5	102.9	80.2	79.7	16.7	99.2	96.6	47.9	84.9	142.7	30.8	**74.37%**

Note: The variance decomposition uses a monthly VAR of order 3 to capture the quarterly trend. 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.

Table 3: Spillover Index, NPL ratio / Commercial loans

	From													
To	BBVA	Bnmex	Std	HSBC	Bnte	Scotia	Inbrs	Bajio	IXE	Bregio	Afirme	Mifel	Bansi	Contribution From Others
Panel A: 1 month														
BBVA	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Banamex	0.4	99.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
Santander	0.3	0.4	99.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7
HSBC	0.6	3.5	1.1	94.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.2
Banorte	1.0	0.4	0.6	0.2	97.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2
Scotia	0.0	3.0	3.4	0.0	1.1	92.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.5
Inbursa	1.7	0.6	0.4	1.7	0.4	0.0	95.2	0.0	0.0	0.0	0.0	0.0	0.0	4.8
Bajio	0.1	1.1	0.4	0.0	20.1	0.1	4.8	73.4	0.0	0.0	0.0	0.0	0.0	26.6
IXE	1.1	0.0	16.9	0.3	3.0	2.8	1.7	0.0	74.3	0.0	0.0	0.0	0.0	25.7
Banregio	0.5	0.7	0.6	0.6	0.1	0.2	0.4	0.9	1.1	94.9	0.0	0.0	0.0	5.1
Afirme	1.2	2.2	0.1	0.8	0.0	0.1	2.8	1.6	0.0	3.4	87.8	0.0	0.0	12.2
Mifel	1.5	3.6	1.2	1.7	0.1	0.0	1.8	2.1	3.5	0.9	0.2	83.4	0.0	16.6
Bansi	1.3	0.0	0.4	5.2	5.0	7.1	0.2	0.2	0.4	0.0	1.7	0.8	77.8	22.2
Contribution to others	9.7	15.5	25.0	10.4	29.8	10.2	11.6	4.8	5.1	4.3	1.9	0.8	0.0	129.2
Contrib. includ. own	109.7	115.1	124.3	105.2	127.6	102.7	106.8	78.2	79.4	99.3	89.7	84.2	77.8	**9.94%**
Panel B: 12 months														
BBVA	22.9	2.6	2.3	26.7	11.5	2.7	10.9	1.2	3.5	2.9	9.8	1.8	1.2	77.1
Banamex	15.6	55.9	0.1	6.9	2.1	1.7	1.9	4.6	0.6	2.6	1.1	1.3	5.6	44.1
Santander	6.5	0.9	46.5	0.7	16.3	6.8	3.9	2.5	7.1	1.8	0.4	2.1	4.5	53.5
HSBC	2.4	1.4	0.3	57.4	15.5	15.1	1.0	0.4	0.1	1.7	0.5	0.3	3.9	42.6
Banorte	9.3	2.9	4.0	0.9	61.3	2.0	0.3	3.6	7.1	2.1	1.4	3.7	1.4	38.7
Scotia	4.0	1.8	2.6	8.6	15.5	39.0	5.2	3.7	7.7	0.9	0.9	1.0	9.2	61.0
Inbursa	4.5	4.6	1.6	3.3	6.0	0.2	67.9	0.6	0.5	1.8	6.9	0.5	1.6	32.1
Bajio	2.8	2.0	1.1	4.7	36.3	5.7	9.9	16.9	1.3	5.6	4.4	5.2	4.0	83.1
IXE	1.4	8.3	13.0	4.2	2.8	4.4	9.7	4.9	47.9	0.4	0.8	0.9	1.5	52.1
Banregio	3.2	1.1	0.9	3.6	7.3	10.4	15.1	3.7	1.0	34.5	7.7	3.7	7.9	65.5
Afirme	1.0	3.1	0.2	1.0	0.3	3.3	40.9	2.1	0.2	3.9	40.9	3.0	0.4	59.1
Mifel	1.3	1.3	0.7	15.9	2.0	14.9	3.1	5.2	7.4	5.6	4.5	32.6	5.6	67.4
Bansi	4.9	0.7	2.2	9.6	17.3	4.8	10.9	0.4	2.1	0.7	12.6	2.4	31.6	68.5
Contribution to others	56.9	30.4	29.0	86.0	133.1	71.7	112.6	32.7	38.7	29.8	51.1	25.8	46.9	744.8
Contrib. includ. own	79.8	86.3	75.5	143.4	194.4	110.7	180.5	49.6	86.6	64.3	92.0	58.4	78.5	**57.29%**
Panel C: 60 months														
BBVA	17.5	3.7	2.1	24.8	15.9	3.5	8.9	2.3	3.8	3.3	8.9	1.2	4.2	82.5
Banamex	8.1	24.9	0.2	25.1	11.2	11.5	3.4	3.1	1.1	3.1	1.9	0.8	5.6	75.1
Santander	6.2	1.1	38.7	4.5	16.4	6.3	7.3	2.2	6.3	1.8	2.5	1.8	4.9	61.3
HSBC	3.4	1.2	0.5	38.7	16.8	16.1	7.1	2.1	1.5	4.3	3.8	0.5	4.2	61.3
Banorte	8.9	4.0	3.8	1.3	57.2	3.1	1.7	3.7	7.8	2.1	1.5	3.5	1.6	42.8
Scotia	4.3	2.1	2.7	8.6	13.6	33.3	7.7	4.3	8.3	1.4	4.6	1.0	8.0	66.7
Inbursa	4.8	4.8	1.5	4.9	6.8	1.8	61.2	0.8	0.6	2.1	7.3	0.5	2.8	38.8
Bajio	1.7	1.6	0.7	4.5	21.3	10.6	26.1	10.1	1.2	4.5	11.7	3.4	2.6	89.9
IXE	1.3	10.2	12.0	4.3	2.8	5.0	11.3	5.5	43.7	0.4	1.0	0.8	1.7	56.3
Banregio	3.9	0.8	0.7	9.3	13.5	8.1	16.5	2.5	1.0	22.4	11.8	2.8	6.8	77.6
Afirme	1.2	2.1	0.1	0.6	0.4	5.4	46.8	2.2	0.4	4.0	33.2	2.4	1.2	66.8
Mifel	1.7	1.0	0.5	12.8	3.1	13.8	12.3	4.5	6.1	4.9	8.0	25.8	5.5	74.3
Bansi	6.6	0.6	1.7	11.5	19.7	5.4	10.6	0.5	1.8	1.2	13.7	1.7	25.1	74.9
Contribution to others	51.9	33.1	26.5	112.4	141.4	90.6	159.7	33.5	39.9	33.1	76.6	20.5	49.0	868.2
Contrib. includ. own	69.5	58.0	65.3	151.1	198.5	123.9	220.9	43.6	83.6	55.6	109.8	46.2	74.1	**66.78%**

Note: The variance decomposition uses a monthly VAR of order 3 to capture the quarterly trend. 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.

Table 4: Spillover Index, NPL ratio / Consumer loans

To	From														
	BBVA	Bnmex	Std	HSBC	Bnte	Scotia	Inbrs	Bajio	IXE	Bregio	Afirme	Amex	Mifel	Bansi	Contribution From Others
Panel A: 1 month															
BBVA	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Banamex	3.2	96.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.2
Santander	8.4	0.0	91.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.3
HSBC	0.6	0.0	0.3	99.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9
Banorte	2.0	0.0	0.1	0.0	97.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.1
Scotia	5.8	0.1	0.6	0.5	1.8	91.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.7
Inbursa	0.8	0.1	2.1	0.3	2.8	1.2	92.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.2
Bajio	7.3	0.0	0.0	0.5	1.1	1.1	1.1	89.0	0.0	0.0	0.0	0.0	0.0	0.0	11.0
IXE	1.9	0.4	0.9	1.0	3.6	4.0	0.1	0.1	88.1	0.0	0.0	0.0	0.0	0.0	11.9
Banregio	0.2	0.8	2.3	0.8	1.1	0.3	0.4	0.6	1.8	91.8	0.0	0.0	0.0	0.0	8.2
Afirme	2.3	0.4	0.1	0.0	1.0	2.0	0.0	1.9	0.8	0.0	91.5	0.0	0.0	0.0	8.5
Amex	0.0	1.0	2.2	0.3	0.3	5.0	7.8	1.7	0.6	1.4	1.5	78.1	0.0	0.0	21.9
Mifel	0.9	15.2	1.6	0.1	0.1	0.2	0.9	0.1	0.0	1.7	0.8	1.0	77.5	0.0	22.5
Bansi	0.0	0.5	4.3	0.0	0.8	1.0	0.1	1.2	8.1	1.4	0.6	0.4	1.2	80.5	19.5
Contribution to others	33.3	18.5	14.4	3.5	12.5	14.7	10.3	5.6	11.3	4.5	2.9	1.4	1.1	0.0	134.1
Contrib. includ. own	133.3	115.3	106.0	102.5	110.3	106.0	103.1	94.6	99.4	96.4	94.4	79.5	78.6	80.5	**9.58%**
Panel B: 12 months															
BBVA	33.8	8.3	17.3	1.4	0.4	8.1	0.8	0.0	2.2	10.3	10.7	1.6	3.5	1.5	66.2
Banamex	3.7	54.2	6.6	0.6	0.8	10.0	1.6	0.2	0.2	5.8	1.5	6.2	3.2	5.3	45.8
Santander	6.9	8.7	32.8	0.5	2.0	13.5	2.9	0.5	0.3	10.9	10.5	3.4	5.5	1.7	67.2
HSBC	1.4	13.4	0.7	73.5	0.2	0.2	2.2	0.5	0.9	4.0	1.0	1.3	0.4	0.5	26.5
Banorte	8.0	1.6	10.8	3.3	45.3	1.6	0.7	0.1	11.3	9.2	2.1	0.7	2.0	3.4	54.7
Scotia	0.8	5.9	8.4	0.2	8.8	46.9	10.1	0.1	0.6	0.8	12.9	0.5	1.8	2.4	53.1
Inbursa	0.5	20.7	2.5	3.1	20.1	5.5	38.7	0.1	0.9	2.1	0.4	1.2	2.2	2.2	61.3
Bajio	23.0	1.7	2.3	38.1	1.2	1.9	0.7	10.2	0.8	7.3	5.5	4.3	2.8	0.3	89.8
IXE	1.4	1.1	3.1	1.6	13.0	11.5	2.6	0.2	48.8	1.5	2.6	2.4	3.2	6.9	51.2
Banregio	1.0	0.3	6.8	17.8	4.5	8.9	1.5	0.6	1.2	43.1	3.2	3.6	7.4	0.2	56.9
Afirme	1.4	3.6	5.2	1.5	2.6	4.4	1.5	3.3	3.5	0.7	65.4	1.5	4.0	1.6	34.6
Amex	0.8	9.8	7.3	9.7	10.1	14.5	11.0	2.3	0.5	4.6	1.9	20.4	4.6	2.7	79.7
Mifel	0.9	1.6	27.6	2.0	2.1	1.6	6.9	0.1	1.5	3.9	6.4	2.1	35.3	7.9	64.7
Bansi	1.6	1.4	3.1	8.6	2.1	2.7	0.5	1.7	7.0	11.1	4.0	0.9	10.9	44.2	55.8
Contribution to others	51.2	77.9	101.7	88.6	67.8	84.4	43.1	9.6	30.8	72.1	62.6	29.7	51.4	36.5	807.5
Contrib. includ. own	85.0	132.1	134.5	162.0	113.1	131.3	81.8	19.8	79.6	115.2	128.0	50.0	86.7	80.7	**57.68%**
Panel C: 60 months															
BBVA	12.3	8.2	17.5	6.5	3.8	8.3	5.0	0.2	1.3	10.6	6.9	4.2	10.3	5.0	87.7
Banamex	1.6	20.1	15.3	9.1	2.8	8.0	3.8	0.6	0.9	11.9	3.7	6.8	9.9	5.4	79.9
Santander	2.6	5.5	24.0	4.8	6.4	10.4	6.6	0.4	0.6	11.7	6.4	3.8	11.5	5.2	76.0
HSBC	1.0	13.4	5.5	47.7	1.1	3.0	3.4	0.6	0.9	6.9	2.4	5.9	4.9	3.5	52.3
Banorte	4.6	4.1	12.5	7.3	27.5	5.8	5.6	0.2	6.7	9.2	3.3	2.5	6.1	4.6	72.5
Scotia	0.4	5.9	5.7	12.1	12.6	28.0	8.4	0.2	0.5	8.7	8.1	1.2	3.2	4.9	72.0
Inbursa	0.4	15.3	5.2	13.3	12.7	10.2	21.2	0.4	0.7	6.3	3.2	3.4	4.2	3.3	78.8
Bajio	13.9	5.0	7.3	24.1	6.6	4.6	6.2	6.3	0.6	6.8	4.7	4.0	7.0	3.0	93.7
IXE	0.9	2.3	3.7	9.0	12.8	15.4	3.8	0.3	30.5	5.4	4.8	2.2	3.2	6.0	69.6
Banregio	0.7	0.5	16.0	14.1	5.7	12.4	2.6	0.4	0.8	24.3	8.3	3.4	8.9	1.7	75.7
Afirme	1.3	6.3	5.2	3.5	2.7	4.2	2.0	3.0	3.3	1.3	57.8	2.7	4.5	2.3	42.2
Amex	0.6	10.6	7.3	8.9	14.1	15.2	11.8	0.5	0.5	7.8	3.2	4.4	7.5	7.8	95.6
Mifel	0.7	3.1	26.3	2.4	5.2	6.2	6.6	0.3	1.3	8.9	5.8	3.6	23.3	6.3	76.7
Bansi	1.2	5.9	6.8	13.1	4.7	5.6	5.4	1.1	4.1	8.4	4.2	1.2	11.0	27.4	72.6
Contribution to others	30.1	86.0	134.1	128.4	91.1	109.3	71.2	8.2	22.1	103.9	64.9	45.0	92.1	58.9	1045.3
Contrib. includ. own	42.4	106.1	158.0	176.0	118.6	137.3	92.4	14.5	52.5	128.2	122.8	49.3	115.4	86.4	**74.67%**

Note: The variance decomposition uses a monthly VAR of order 3 to capture the quarterly trend. 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.

Table 5: Spillover Index, NPL ratio / Mortgage loans

To	From												
	BBVA	Bnmex	Std	HSBC	Bnte	Scotia	Inbrs	Bajio	IXE	Bregio	Afirme	Mifel	Contribution From Others
Panel A: 1 month													
BBVA	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Banamex	10.8	89.2	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.8
Santander	37.7	10.0	52.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	47.8
HSBC	1.5	0.4	0.7	97.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.6
Banorte	3.2	1.6	0.3	0.2	94.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.2
Scotia	4.7	1.0	0.6	4.0	3.4	86.4	0.0	0.0	0.0	0.0	0.0	0.0	13.6
Inbursa	0.7	0.1	0.0	4.1	4.1	0.3	90.8	0.0	0.0	0.0	0.0	0.0	9.2
Bajio	0.7	0.1	0.0	0.1	0.0	0.2	0.8	98.1	0.0	0.0	0.0	0.0	1.9
IXE	4.4	0.7	0.9	0.0	3.3	0.1	6.3	0.0	84.3	0.0	0.0	0.0	15.7
Banregio	0.5	1.2	0.9	0.0	0.0	1.5	0.2	3.4	0.0	92.3	0.0	0.0	7.7
Afirme	1.1	1.5	0.6	0.0	0.1	0.4	1.2	0.2	0.1	2.7	92.3	0.0	7.8
Mifel	0.0	1.2	1.6	0.0	0.1	0.8	0.0	1.1	0.0	7.6	2.1	85.5	14.5
Contribution to others	65.3	17.7	5.5	8.3	10.9	3.3	8.5	4.6	0.1	10.3	2.1	0.0	136.7
Contrib. including own	165.3	106.9	57.8	105.8	105.7	89.7	99.3	102.8	84.4	102.6	94.3	85.5	**11.39%**
Panel B: 12 months													
BBVA	70.2	8.5	0.7	1.2	1.0	6.2	1.8	0.9	5.7	1.1	1.9	0.8	29.8
Banamex	22.6	48.8	3.0	2.2	16.7	0.1	0.8	0.8	0.7	2.1	0.3	2.0	51.2
Santander	43.6	4.9	21.8	0.5	24.9	0.3	0.1	0.6	1.6	0.0	0.3	1.3	78.2
HSBC	10.4	29.9	10.7	27.0	3.2	5.3	2.7	3.4	4.1	2.4	0.3	0.8	73.0
Banorte	2.3	0.3	0.9	0.2	92.7	1.4	0.4	0.2	0.2	0.1	1.1	0.3	7.3
Scotia	4.6	34.2	8.5	4.4	14.5	18.9	2.9	0.3	3.6	5.5	1.3	1.3	81.1
Inbursa	7.9	3.9	6.8	5.0	2.8	2.9	63.9	0.2	5.8	0.2	0.4	0.4	36.1
Bajio	1.4	0.7	1.2	0.5	0.2	0.2	3.6	66.5	0.2	17.6	2.5	5.5	33.5
IXE	5.9	10.9	2.0	0.8	25.8	0.6	4.7	0.7	47.2	0.9	0.5	0.2	52.8
Banregio	3.9	0.8	2.0	0.4	0.0	0.6	7.5	47.1	0.2	24.5	12.2	0.7	75.5
Afirme	7.2	1.9	3.4	3.8	0.8	10.0	2.9	33.8	0.2	6.3	23.6	6.1	76.4
Mifel	5.1	1.1	0.9	0.9	0.2	5.8	6.4	34.2	0.3	17.7	2.5	24.9	75.1
Contribution to others	114.9	97.3	40.0	19.8	90.2	33.2	33.8	122.1	22.5	53.8	23.3	19.3	670.1
Contrib. including own	185.1	146.0	61.8	46.7	182.9	52.1	97.7	188.6	69.7	78.3	46.9	44.2	**55.84%**
Panel C: 60 months													
BBVA	25.9	17.5	4.4	0.9	18.5	9.0	2.3	12.7	3.2	1.8	1.0	2.8	74.1
Banamex	17.5	36.5	3.8	1.8	19.7	0.8	4.3	9.4	1.7	2.1	0.9	1.4	63.5
Santander	33.0	12.2	16.3	0.8	28.6	1.9	1.2	2.0	2.3	0.4	0.3	1.0	83.7
HSBC	4.0	15.4	5.7	9.1	15.5	7.0	4.3	31.0	1.6	1.4	0.3	4.8	90.9
Banorte	2.1	0.9	1.1	0.2	90.5	1.9	0.6	0.4	0.2	0.3	1.6	0.3	9.5
Scotia	1.5	17.0	5.5	1.3	27.4	11.7	3.6	24.2	1.3	1.6	0.7	4.3	88.3
Inbursa	9.6	6.5	7.2	4.3	5.3	4.5	53.1	2.4	5.2	0.3	0.5	1.1	46.9
Bajio	3.3	4.7	3.8	1.3	7.1	0.4	8.5	50.7	0.6	9.0	4.9	5.7	49.3
IXE	5.1	12.7	3.2	0.8	25.9	1.8	4.6	6.1	37.6	0.7	0.6	0.9	62.4
Banregio	2.4	1.4	1.4	0.7	1.4	1.1	11.9	62.5	0.4	6.9	4.5	5.4	93.1
Afirme	3.4	0.5	0.6	1.1	0.9	3.1	12.1	66.3	0.3	1.0	3.0	7.7	97.0
Mifel	2.5	0.9	0.6	0.7	0.6	2.6	12.0	66.2	0.4	2.6	1.2	9.6	90.4
Contribution to others	84.3	89.6	37.5	14.0	150.9	34.1	65.3	283.2	17.5	21.3	16.3	35.2	849.3
Contrib. including own	110.2	126.1	53.8	23.1	241.5	45.8	118.4	333.9	55.1	28.1	19.3	44.8	**70.77%**

Note: The variance decomposition uses a monthly VAR of order 3 to capture the quarterly trend. 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.