Banco de México

Working Papers

N° 2021-26

Revisiting the link between systemic risk and competition based on network theory and interbank exposures

Enrique Bátiz-Zuk
Banco de México

José L. Lara-Sánchez
Banco de México

December 2021

Documento de Investigación
2021-26

Working Paper
2021-26

Revisiting the link between systemic risk and competition based on network theory and interbank exposures*

Enrique Bátiz-Zuk[†]
Banco de México

José L. Lara-Sánchez[‡]
Banco de México

Abstract: This paper examines the link between bank competition measures and risk indicators using quarterly interbank exposures data for all banks in Mexico during 2008Q1-2019Q1. The classical literature focuses on disentangling the link between competition and individual bank solvency risk. In this paper, we take one step forward in analyzing the relationship between competition and systemic risk. We use counterfactual bank-level contagion risk indicators as a proxy of systemic risk to assess their relationship with traditional competition measures. Our main finding indicates a negative relationship between the bank-level Lerner index and systemic risk. This means that an increase in competition is associated with an increase in systemic risk. Additionally, we find that the implementation of regulatory reform during the period studied does not affect this relationship.
Keywords: Bank competition, systemic risk, financial contagion, financial stability, network models.
JEL Classification: C23, D40, G21, G28, L14, L16, L22

Resumen: Este documento evalúa el vínculo entre las medidas de competencia bancaria y los indicadores de riesgo utilizando datos trimestrales de exposiciones interbancarias para todos los bancos en México durante el periodo de 2008T1 a 2019T1. La literatura clásica se centra en clarificar el vínculo entre la competencia y el riesgo de solvencia de los bancos individuales. En esta investigación, se avanza analizando la relación entre competencia y riesgo sistémico. Se utilizan indicadores contrafactuales de riesgo de contagio como proxy de riesgo sistémico para estudiar su relación con medidas tradicionales de competencia. El principal hallazgo es que existe una relación negativa entre el índice de Lerner a nivel de banco y el riesgo sistémico. Esto significa que un incremento en la competencia se asocia con un incremento del riesgo sistémico. Además, se encuentra que la implementación de la reforma regulatoria durante el periodo de estudio no afecta esta relación.
Palabras Clave: Competencia bancaria, riesgo sistémico, contagio financiero, estabilidad financiera, modelos de red.

---

*We would like to thank two anonymous referees for their valuable comments and suggestions. We thank Luis Onésimo Leonardo Escobar for excellent research assistance related to bank-level systemic risk indicators.

[†] Dirección General de Estabilidad Financiera. Email: ebatiz@banxico.org.mx.

[‡] Dirección General de Estabilidad Financiera. Email: jose.lara@banxico.org.mx.

1 Introduction

A vast body of literature has addressed the theoretical and empirical nature of the relationship between competition and risk taking at the bank level.[1] As a result, the so-called individual-bank or solvency-risk-competition nexus has been investigated, and two opposing hypotheses have been the subject of debate. The "competition-stability" hypothesis (see Boyd and De Nicolo (2005)) argues that more intense competition contributes to financial stability in the banking sector. The principle supporting this theory is that as the pressure on banks to compete increases, lending rates decrease, which benefits banks' standalone levels of credit risk. In contrast, the "competition-fragility" hypothesis (see Keeley (1990)) argues that increased competition negatively affects the stability of the financial system. The rationale behind this proposition is that banks' search for yield leads to excessive risk taking, which eventually exerts a negative impact on the resilience of the banking sector. The focus in the literature is on empirically testing which of these two hypotheses holds in practice. As expected, the challenge is that in real-world applications, the results vary based on several factors. To date, there is no academic agreement on which of the two opposing views is true because the empirical results are mixed (see Zigraiova and Havranek (2016)). Interestingly, it has been postulated that these two hypotheses may coexist in a nonlinear framework (see Martinez-Miera and Repullo (2010)). However, the evidence for this hypothesis is also mixed.[2] This body of literature also examines how the regulatory framework (see Beck et al. (2013) or the country's regulatory environment (see Anginer et al. (2014)) affects bank competition and whether it intensifies or attenuates the relationship between competition and systemic risk.

Although we have empirical estimates of the "competition-stability" link dating back to 2000, the results based on bank-level standalone risk measures do not converge, and there is no consensus (see Zigraiova and Havranek (2016)). In fact, there is significant heterogeneity in the empirical results reported in the literature. Part of the reason for this heterogeneity is that studies differ in terms of (i) variables' definitions related to the banks' standalone risk and bank competition; (ii) choice of data (e.g., length of sample) or coverage type (e.g., global, regional, or single-country); (iii) methodology and estimation framework (e.g., dynamic or static models; standard linear panel models or quantile regression); and (iv) choice of control variables. Zigraiova and Havranek (2016) collected 598 empirical estimates of the rela-

[1] See popular literature surveys by Carletti (2008) and Degryse and Ongena (2008).

[2] Brei et al. (2020) provides a summary of studies that assess the validity of the Martinez-Miera and Repullo (2010) model to characterize the solvency-risk-competition nexus.

tion between competition and bank risk taking from 31 studies between 2003 and 2014 and performed a meta-analysis. The results did not reveal any evidence of a robust relationship between competition and banks' standalone risk.

A noteworthy limitation of this literature is that most papers analyze only average individual or standalone bank risk and ignore each bank's contribution to the overall systemic risk of the banking sector. In this regard, recent literature has focused on systemic risk arising from correlation risk (e.g., Anginer et al. (2014), Leroy and Lucotte (2017), Silva-Buston (2019), Hirata and Ojima (2020)). To the best of our knowledge, other sources of systemic risk, such as concentration or contagion risk stemming from the topology of the interbank market and the bank's systemic importance and its degree of interconnection, have not been analyzed. When assessing the relationship between risk and competition at the banking sector level, the benefits and caveats of being either a global systemically important bank (G-SIB) or a domestic systemically important bank (D-SIB) should be considered. In fact, the level of each individual bank's solvency risk differs significantly in any banking sector because of the bank's size, degree of interconnection, and substitutability. Moreover, the behavior of both groups is inherently heterogeneous, which may drive the relationship among them in several different ways that could be difficult to predict.

In this paper, the empirical relationship between bank competition and systemic risk from the resulting contagion is examined from a new and innovative angle using network theory and a linear regression dynamic model (see Arellano and Bond (1991)). Our main contribution is that we use systemic risk measures at the bank level calculated from financial contagion counterfactual algorithms and expand the evidence beyond the individual banks' standalone risk to analyze the link between competition and contagion risk. Regarding banks' risk-taking behavior, we examine contagion risk measured at the bank level as the sum of the maximum counterfactual losses of the banking sector from each idiosyncratic bank failure and use as competition measure, bank-level Lerner indices. Additionally, we analyze and provide empirical evidence of the effect of a regulatory reform implemented in 2014 that was especially designed to boost competition among banks (see Bátiz-Zuk and Lara-Sánchez (2022)). For completeness, our analysis includes the nexus between bank-individual risk and competition. Solvency risk is measured using the Z-score and the non-performing loan ratio, whereas competition is measured at the bank level. Moreover, we perform several robustness tests. In this regard, we innovate and depart significantly from the standard literature that has focused on standalone bank risk (Zigraiova and Havranek (2016)) and, more recently, on correlation risk measures (Anginer et al. (2014), Leroy and Lucotte (2017), Silva-Buston (2019), and Hirata and Ojima (2020)) as proxies for systemic risk.

In the literature, there are many systemic risk measures, and the choice among them is challenging because each measure may capture a different source or dimension of systemic risk. We use network theory and analyze three popular systemic risk indicators at the bank level. Specifically, we follow Guerrero-Gómez and Lopez-Gallo (2004) and use a sequential default algorithm originally developed by Furfine (2003) that is useful for tracing the path of a contagion from a trigger bank to other banks during several contagion rounds. This algorithm has been used in many studies on the Mexican banking sector (see Bátiz-Zuk et al. (2016) and references therein) to quantify the banking sector counterfactual aggregate contagion loss arising from the idiosyncratic bank failure.

Our systemic risk measures have the following elements: (i) they are widely accepted and documented in the literature (e.g., Upper (2011) and Upper and Worms (2004)); (ii) they are largely propagated in academia and central banks; (iii) they serve as a comprehensive measure of systemic risk for the entire domestic banking sector; (iv) they comprise individual bank-specific risk measures; and (v) they capture both contagion and concentration risk stemming from network structure and the degree of interconnections across multiple institutions. To our knowledge, this paper is the first to explore the relationship between bank-level measures related to network theory counterfactual systemic risk and competition for a single country over a relatively long period. Our bank-level proprietary quarterly data are collected by Mexican financial authorities and cover the period from 2008:Q1 to 2019:Q1.

Following Beck et al. (2013) and Anginer et al. (2014), we also study the effect of a regulatory reform over both risk dimensions (i.e., systemic and solvency risk) on competition. The consensus is that studying the impact of regulation on the solvency risk of individual banks is insufficient because a bank's failure may trigger systemic risk in the banking sector, which will exert a negative effect on the banking sector and, ultimately, on the financial system. We study the impact of a domestic financial regulatory reform implemented in 2014. This issue is relevant because regulatory changes affect banks' risk-taking incentives, which may negatively affect the stability of the banking sector. Moreover, it is important to consider the systemic dimension of risk when designing regulation to promote an efficient competition policy.

We focus on domestic rather than international reforms for the following reason. Although the global financial crisis led to a revamp of the regulatory framework that promoted the study on the impact of regulatory shocks with a focus on macroprudential policies (see Galati and Moessner (2013)), Mexico had already implemented almost all of the new capital rules after the 1995 Tequila crisis. The counter-cyclical capital buffer and the liquidity risk regulation—and other macroprudential measures introduced in Basel III—were adopted in Mexico, but there is no reason to believe that these had a more powerful impact on the risk-competition nexus than the 2014 financial reform, which was especially designed to promote competition.[3] According to the literature, the effect of the regulatory framework on banks' behavior and, ultimately, on the stability of the banking sector is inconclusive. Bátiz-Zuk and Lara-Sánchez (2022) use the bank-level Lerner index and find that the regulatory reform had a positive average effect and increased banks competition intensity in a few years. However, they also report significant heterogeneity, as large banks gained greater market power. For systemic risk purposes, this finding may have an enigmatic effect that is worth studying.

Our main finding is the negative linear relationship between our individual Lerner index and our bank-level systemic risk indicators. This result somehow supports the "competition-fragility" hypothesis from a macroprudential perspective because systemic risk decreases as market power increases (i.e., the Lerner index increases). Moreover, we report estimates excluding and including control variables for a variety of bank characteristics and macroeconomic factors that may affect the sign, significance, and magnitude of the coefficient, as suggested by Anginer et al. (2014). Additionally, we find no relationship between our individual Lerner index and our bank-level solvency risk indicators. This result is unsurprising and consistent with the findings of Zigraiova and Havranek (2016), where little interplay is well-documented between competition and individual bank risk. In addition, we find that the 2014 financial regulatory reform exerts no effect on the systemic-risk-competition nexus. We conclude that more evidence is needed from either banking sectors in other countries or a sample of international banks.

The literature relating bank-level systemic risk measures with bank competition is in its infancy. However, as with the solvency-risk-competition nexus, early studies suggest that evidence is also mixed for the systemic-risk-competition nexus. Anginer et al. (2014) use multi-country data and apply the Merton (1974) contingent claim pricing method to quantify the bank's default risk based on a structural model known in the credit risk literature as distance-to-default (DD). They use market bank-level systemic risk indicators, including the condi-

[3] See Bátiz-Zuk and Lara-Sánchez (2022) for details of the effect of the financial reform.

tional value at risk measure (CoVaR), to compute each bank's contribution to systemic risk (see Adrian and Brunnermeier (2011)) and study the credit risk codependence using quantile regressions. Leroy and Lucotte (2017) investigate the competition-stability trade-off using SRISK[4] as a proxy for bank-level systemic risk for a sample of European banks. Silva-Buston (2019) explores the sources of systemic risk using the marginal expected shortfall (MES) as a proxy for bank-level systemic risk for a sample of European banks. The main virtue of this paper is that it distinguishes among different sources of systemic risk, such as interbank commonality[5], the systematic component,[6] and the excess component.[7]

The main finding of all of these studies (i.e., Anginer et al. (2014), Leroy and Lucotte (2017), and Silva-Buston (2019)) is that a negative relationship exists between bank competition and systemic risk, which is consistent with the "competition stability" paradigm at the macroprudential level. In other words, these papers' main finding is that competition improves stability as systemic risk is reduced. This result arises because less competitive pressure tends to increase the correlation in banks' risk-taking behavior. In all of these papers, correlations between banks' risk-taking decisions are affected by an increase in competition, which impacts both individual banks and systemic risk. In contrast, Hirata and Ojima (2020) use CoVaR for a sample of Japanese regional banks and report the opposite finding that more intense competition leads to higher systemic risk. The key difference between all of these reviewed studies and ours is that the studies in the literature focus on systemic risk attributable to correlation risk, whereas we assess the role of contagion risk. Unfortunately, the aforementioned approaches are not useful for characterizing risk across banks that do not have market data, which is the case for banks that are not listed on domestic stock exchanges.

Unfortunately, in Mexico, the use of market bank-level systemic risk indicators is limited because the vast majority of domestic banks and foreign bank subsidiaries are not publicly listed on the Mexican stock market. Network theory is not limited to data available exclusively for listed banks, so it is an ideal framework to measure in a comprehensive manner systemic risk arising from interbank interconnections for banking sectors in different countries. Moreover, in this paper, we consider almost all domestic and foreign-owned Mexican banks classified as

[4]In contrast to MES, SRISK considers both bank size and liability. Intuitively, SRISK is a measure of the bank's expected capital shortfall during a crisis event that affects the banking sector.

[5]The interbank commonality can be understood as the co-movement between the bank's stock price return and the banking-sector index return in the tail of the system's loss distribution.

[6]The systematic component can be understood as the co-movement of the bank's stock price return with the market index stock price return in the tail of the market's loss distribution.

[7]This can be regarded as a residual and a different source of commonality.

commercial banks. We exclude micro-financing entities, government loan institutions (e.g., development banks), multi-governmental banks, securities firms, and non-bank financial intermediaries (NBFI). Even though we exclude a few banks in the Mexican banking sector because of a number of data restrictions, we report that the overall coverage of our sample is extremely satisfactory and inclusive.

Compared with other single-country studies available in the literature, our empirical analysis includes a higher number of banks that vary in terms of systemic importance, business model, and ownership structure (i.e., our sample includes both publicly listed and privately owned banks).[8] For example, although Berger et al. (2009), Jiménez et al. (2013), and de Ramon et al. (2020) analyze the relationship between competition and risk taking only for deposit-taking institutions, we adopt a broader scope and include other bank types, such as investment or niche banks. Following Bátiz-Zuk and Lara-Sánchez (2022), we believe that this approach is appropriate for at least two reasons. First, large banks compete in both investment and deposit-taking activities. This fact adds complexity because, in practice, computing reliable competition measures (e.g., the Lerner index) that distinguish adequately between the share of the cost attributable to deposit taking from investment costs is not possible. Because large banks compete in both activities, we believe that it is best to include investment banks. Second, in terms of the accuracy of systemic risk counterfactual measures, including as many banks as possible is best, especially those with different business models or trading activities, because the failure of any financial institution may trigger subsequent failures of other entities through multiple contagion channels, as illustrated by Upper (2011).

Our focus on Mexico is motivated by three factors. First, our paper cannot be completed using multi-country data because of the confidential nature inherent to interbank exposures. Second, our study offers a unique country-level contribution to the literature considering that, to the best of our knowledge, no other country has time series data on direct contagion risk variables for a sufficiently long period. Third, although our data cover the global financial crisis, in Mexico, this period did not exert a dramatic impact in terms of systemic risk that requires specialized econometric treatment to take into account this adverse scenario.[9] In fact, this period can be broadly characterized as a global liquidity shock that led to a drought in

[8]Our paper differs from other studies (e.g., Beck et al., 2006, and Schaeck et al., 2009) that have investigated how competition influences either the risk level or the probability of having a systemic crisis.

[9]It is well known that a set of events, such as government interventions, public bailouts, and events involving central banks' liquidity, exists and supports actions that exert a negative impact on both competition and risk-taking incentives (e.g., see Hakenes and Schnabel, 2010)

the availability of funds in debt markets. As a response, Mexican banks faced difficulties and had to reduce their lending, but no bank failure occurred.

The remainder of this paper is organized as follows. Section 2 describes the Mexican interbank structure and the theoretical mechanism to explain possible transmission channels between systemic risk and competition at the bank level. Section 3 recounts the characteristics of our sample and our variable definitions, along with the methodology used for the baseline model. Section 4 reports our empirical results, including robustness tests, and discusses some implications, assumptions, and caveats. Section 5 concludes.

2 Theoretical mechanisms

This section proceeds as follows. We start by describing the different channels through which systemic risk could arise. Then, we focus on the characteristics of contagion risk as a source of systemic risk and present the "relationship lending" channel. Given the inherent risk between idiosyncratic bank risk failure and crisis episodes, we discuss the supplementary channels presented in previous studies that explore the nexus between competition and systemic risk because these might indirectly influence contagion risk. Next, we provide an overview of the structure of the interbank market. Finally, we provide a summary of other channels described in studies on the link between systemic risk and competition using systemic measures that rely on market data. It is necessary to underscore that in this section, we are not analyzing how competition affects banks' solvency risk or individual stability because this has been documented in the literature with the "competition-stability" (see Boyd and De Nicolo (2005)) and "competition-fragility" (see Keeley (1990)) hypotheses. Note we are not able to quantify the effects of each channel at the individual level. Moreover, it is not possible at this stage to decompose the elements interacting in each mechanism. However, this same problem applies to other theories that intend to explain the interaction mechanisms between systemic risk and competition.

Broadly, systemic risk may arise in the banking sector through four channels. First, correlation risk may appear in the form of a correlated asset shock that impairs banks and other non-bank financial intermediaries in the financial system. Second, the default risk of one bank may trigger direct and indirect defaults of other banks (sequential or contagion risk). Third, the funding illiquidity of one bank may trigger the illiquidity of other banks. Fourth, large asset fire sales by one or multiple impaired banks may trigger a massive sale that leads to an abrupt and unanticipated price distortion (i.e., downward price spiral) that could seriously damage the financial system.

This paper focuses on contagion risk as a source of systemic risk. Upper (2011 p.112) and De Bandt et al. (2009) document that contagion risk can occur through many different asset or liability side channels. In this paper, we focus on direct contagion. Direct contagion may trigger indirect contagion because large losses could lead to bank runs if depositors succumb to herd behavior and withdraw their funds as a result of a panic (Iyer and Peydró-Alcalde (2005)). Some models are available in the literature to address this source of concern (see Upper (2011)). In essence, direct contagion arises if and only if the bank's bilateral aggregate interbank exposures are large compared with the lender's capital. The structure of the interbank network determines the severity of direct contagion risk (see Allen and Gale (2000) and Freixas et al. (2000)). Our systemic risk measure based on direct contagion is limited in the sense that it ignores central bank actions (i.e., external shocks) and relies fully on internally generated shocks. In addition, note that one or more of the channels discussed in this section may lead to an idiosyncratic bank failure. Therefore, a number of channels could cause contagion risk and affect a bank's systemic risk.

In this paper, we attempt to identify the channel that can explain the link between the correlation of fiercer competition on a bank's risk-taking actions that, in turn, affect a bank's lending and financing decisions in the interbank market. Banks perform a number of very different operations in the interbank market to manage liquidity risk. It is impossible at this stage to provide a detailed mapping relating how competition affects each type of trading operation. Perhaps the most important channel that explains the effect of competition on systemic risk in the interbank market is related to "relationship lending"[10]. Depending on competitive pressures and the bank's policy, smaller banks, banks with a relatively high share of non-performing loans, and those with a small amount of deposits depend on relationships with other banks to receive funding (see Cocco et al. (2009)). It is likely that competition effects are heterogeneous among banks, which means that banks' response functions to competition pressures differ. On average, during a non-crisis period, banks may (i) expand and diversify operations with their trading counterparts; (ii) intensify their operation volumes with the actual counterparts; and (iii) reduce counterparts, which would lead to an increase of concen-

[10] There is a large body of literature on trading relationships in the interbank market (e.g., Iori et al., 2007, Cocco et al., 2009, Affinito, 2012, Afonso et al., 2013, Bräuning and Fecht, 2017, Craig et al., 2015).

tration risk. Note that (ii) and (iii) are associated with an increase in systemic risk as measured by direct contagion at the bank level, whereas (i) implies a reduction in systemic risk. Note that the process of trading with different partners also depends on market information and the bank's performance and reputation. Additionally, the possibility of a government bailout plays an important role. In the same vein, liquidity assistance programs designed by central banks to assist institutions in crisis or distress periods play a pivotal role.

The mechanism or set of channels that relate market power with bank-level systemic risk measures can be described as follows. To start with, as shown during the previous global financial crisis, as the banking sector becomes more competitive, the search for yield may cause banks to relax their lending standards (see Dell'Ariccia and Marquez (2004)) and choose more risky borrowers characterized by more opaqueness in terms of data quality; banks may also collect less data on borrowers (Hauswald and Marquez (2006)). This idea is also supported by the argument that banks that obtain lower profits as an outcome of more intense competition relax their incentives to monitor (Boot and Thakor (1993); Allen and Gale (2000)). These factors increase the average bank solvency risk and contribute to a more fragile banking sector. We expect that this "search for yield" channel may cause banks to increase their risk taking in the interbank market, which would contribute to increasing systemic risk at the bank level because banks might intensify operations with actual counterparts or even concentrate their operations with a few of them. This line of reasoning assumes that trading relationships in the interbank market remain the same. In contrast, the literature describes "cost-efficiency pressures" that arise as a result of more intense competition that may cause banks to diversify risk to reduce portfolio risk (see Anginer et al. (2014)). These factors decrease the average bank solvency risk and contribute to a more stable or resilient banking sector. We expect that this cost-efficiency pressure channel may cause banks to decrease their risk-taking behavior in the interbank market and expand and diversify risk with other trading counterparts, which would contribute to decreased systemic risk at the bank level. Therefore, depending on the dominating effect, there could be a positive or negative relationship between competition and systemic risk.

As banks grow and expand their businesses, two events develop in tandem. First, stronger competition may lead large banks to design new products (e.g., such as collateralized debt obligations (CDOs)), which may intensify solvency risk. Trading complex financial products such as CDOs also contributes to spreading risk to other financial intermediaries, which may seriously affect the interbank market. We expect that this "innovation" channel is associated with an increase in systemic risk at the bank level. Second, we expect that banks' financing needs in the interbank market increase and that risk-taking incentives may or not modify the bank's trading relationships. Depending on the banks' preferences and requirements to trade with specific counterparts, the concentration of bank-level trading risk may increase (i.e., dense network) or decrease (i.e., sparse network). Banks have two options because they can diversify their financing needs using new and multiple partners; alternatively, it is also likely that they intensify their operations using the same or even a reduced number of bank counterparts and concentrate on a few of them. Here, network topology and bank size play a key role.

Consensus exists in the literature (see Beck et al. (2006) and Levine et al. (2007)) that a bank's size has a strong and positive correlation with institutional complexity. Large bank organizations are characterized by low transparency and the significant use of complex instruments. As a result, large banks tend to increase their activity in the interbank market to meet their financial and investment needs, and the degree of interconnection usually intensifies, albeit in a heterogeneous manner. The development of these two events eventually leads to an increase in concentration risk in the interbank market that intensifies contagion risk at the bank level when one or more large or systemically important banks (SIBs) fail. In contrast, it is also possible to argue that an increase in market power intensity may also lead banks to diversify risks in the interbank market by reducing large bilateral exposures with actual counterparts and expanding trades with other banks, which should mitigate concentration and contagion risks, making the banking sector and the interbank market more resilient to adverse shocks. Furthermore, a change in the competitive environment might lead banks to change their activities and modify their exposures in the interbank market, which could cause some shocks and risks to magnify because the interbank lending market is one of the most important risk channels in which shocks are propagated and amplified (Acemoglu et al., 2015).

Another channel that is well documented is related to the case in which banks succumb to herd behavior in response to competition intensity (Acharya and Yorulmazer (2008)). This "herding" channel has its origin in negative and unexpected news about other banks' status or actions that transmit fear to market participants, which may affect common factors. Ultimately, the herding channel leads to an increase in the bank's funding cost because a bank's significant investment exposure to any common factor inevitably leads to a greater increase in its costs (Acharya and Yorulmazer (2008)). We expect that this channel induces a positive relation between market power and contagion risk at the bank level.

The structure of the interbank market determines how contagion risk frequency and severity evolve over time and how it spreads and intensifies at each point in time in the network. The degree of interconnectedness is determined by the network topology, for which idiosyncratic bank characteristics (e.g., size or capitalization), risk-taking activities, and financing needs of each institution play a key role. The structure of the interbank market determines the sensitivity of the banking sector to the failure of any bank. The topology of the Mexican interbank banking sector can best be described as a "core-periphery" structure[11]. According to this structure, core banks have a relatively high degree of interconnectedness and a low degree of interconnection with a few small banks in the periphery, whereas small banks in the periphery only have direct links to banks in the core. Two key features fully characterize this structure. First, banks in the core play a fundamental role, whereas all other remaining banks play a less important role. Proximity to the core is not the same as bank size, but the probability that a big or D-SIB bank forms part of the core is usually very high. Second, as the financial system evolves over time in a manner similar to a complex adaptive system (Haldane (2013)), the core-periphery structure remains stable over time. This implies that the bank's response may be highly heterogeneous depending on whether it is a D-SIB or a non-DSIB. The exposures between D-SIBs and non-DIBs are also heterogeneous.

In the literature, a set of different channels relate the effect of concentration in the banking sector to systemic risk in the context of correlation risk. Silva-Buston (2019) provides a summary and describes in detail the "monitoring" channel (Allen and Gale (2000)), the "complexity" channel (Beck (2008)), and the "diversification-opportunities" channel (Diamond (1984)). Even though these channels may indirectly affect the interbank market, the design of our measures is limited in that it cannot disclose the individual effect of these channels.

3 Data, methodology, and variable definitions

3.1 Data

In this section, we report the data sources used in our paper. We employ both publicly available and proprietary bank-level financial information collected by Mexican financial authorities (i.e., Banco de México (Banxico, its acronym in Spanish) and the National Banking and

[11] See Craig and Von Peter (2014) for a full description of the core-periphery structure.

Securities Commission (CNBV, its acronym in Spanish)). We obtain proprietary actual data on banks' bilateral exposures to compute bank-level systemic risk indicators. We also use publicly available individual bank balance sheet data to compute standalone risk and competition measures. In addition, we use publicly available macroeconomic information to estimate some of our indicators, such as the Lerner index. Given the large differences in the data related to time frequency, variable definitions, and characteristics, we structure this section as follows. We start with an outline of the scope of our sample. Next, we describe the source of our bank-level systemic risk data. Then, we explain in detail the source of a bank's balance sheet data. Finally, we show how we treat bank mergers and acquisitions and discuss the nature of the consolidated data in our sample.

3.1.1 Sample scope

In this paper, we do not include entities such as credit unions or popular credit and savings entities because they compete to attract customers (e.g., micro-loans) using a business strategy that departs significantly from the activities of traditional banks. Our analysis includes almost all commercial banks in the Mexican banking sector from 2008Q1 to 2019Q1. Our sample period covers a full economic cycle, including the downturn episode related to the global financial crisis. Moreover, our sample includes periods of sector-specific turmoil, such as in mid-2013, when several noteworthy Mexican construction firms filed for bankruptcy (see Iakova et al. (2014) for details). For systemic risk purposes, it is best to include as many banks as possible if we want a fair assessment of the degree of interconnection among bank entities because any bank failure may lead to direct and/or indirect contagion loss. Our paper is limited, as is most of the literature, in that our bank-level systemic risk measures only reflect contagion stemming from direct effects.

In terms of competition, our strategy of including as many banks as possible means that we incorporate entities that compete in both the traditional and non-traditional financial intermediation markets. For bank competition purposes, this approach may in principle be taken as conflicting because all non-structural competition measures used in this paper assume that banks offer homogeneous goods and services (see Leon (2015)). However, Bátiz-Zuk and Lara-Sánchez (2022) show that for the case of Mexico, including both traditional and non-traditional banks when assessing the evolution of competition does not change or alter the results.[12]

3.1.2 Interbank market data to measure systemic risk at the bank level

As highlighted by Cerutti et al. (2014), the type of data is a crucial element for studying a bank's degree of interconnection. In this paper, we use a proprietary dataset originally developed and supported by Banxico that includes detailed, actual, aggregated bilateral interbank exposures (i.e., both on- and off-balance sheet exposures) for all banks that form part of the system. Interbank data are available at a daily frequency. To assess systemic risk, banks in Mexico are requested to complete a number of preset regulatory layouts that register all bank transactions in the interbank market related to both on- and off-balance sheet operations at an individual level.[13] Data are highly confidential because of the sensitivity of their information content, and internal access is restricted and controlled. Data for each individual bank operation are converted to bilateral exposures. There are four exposure types: deposits & loans (i.e., revolving and non-revolving), securities cross-holdings, derivatives, and foreign exchange (FX).

In what follows, we provide a succinct overview of how interbank exposures are computed from each individual operation/transaction depending on the type of instrument/security. We refer the interested reader to Poledna et al. (2015, pp.73-74) for a very detailed description. To compute the daily current exposures between banks i and j, all deposits and loans between them are added. Gross rather than net exposures are computed. Each individual exposure is measured after credit risk mitigation. Daily gross current exposures between banks i and j

[12] Some studies in the literature (e.g., de Ramon and Straughan, 2020) exclude bank entities that do not compete in the traditional intermediation market. However, this approach may be biased because some bank-specific variables that form part of non-structural competition measures, such as the bank benefits of large entities, arise from a bank's activity in both markets. Because it is not possible to isolate costs arising from each bank activity, we support the notion that it is best to incorporate all bank entities irrespective of their business model.

[13] Specifically, eight regulatory layouts are taken into account: deposits and interbank operations in domestic currency or in investment units (OCIMN, its acronym in Spanish), deposits and interbank operations in foreign currency (OCIME, its acronym in Spanish), futures and forwards operations (OFF, its acronym in Spanish), options and warrants (OPTO, its acronym in Spanish), exchange of flows and returns operations (i.e., SWAPS), assets and liabilities in foreign currency by term to maturity and size ("ACLME", its acronym in Spanish), purchase and sale of debt securities (CVT, its acronym in Spanish), and debt securities' repurchase agreement operations (i.e., Repos). The list of layouts is publicly available at `https://www.banxico.org.mx/waFormulariosDGASF/wwwNoLeftNavInvBM.jsp`; accessed on September 25, 2020. These layouts are managed and validated by the statistics unit at Banxico's financial stability division. The information is validated using daily, weekly, and monthly regulatory reports (for more details, see Poledna et al. 2015, pp.73-74).

are also calculated for the cross-holdings of securities. For a derivative contract between any two banks, each contract is marked to market, and the net exposure (at the contract level) is computed and assigned to the corresponding bank. Then, all of the outstanding net exposures for each day's results are added in the final exposure.[14]

Banco de México performs the role of supervisor and validates the valuation methods at each bank's risk offices. Mexican banks (i.e., standalone international bank subsidiaries or domestic banks) are not allowed by law to trade exotic derivatives. Two types of foreign exchange transactions occur between banks. Banks may trade FX operations using continuous linked settlement (CLS) or without using CLS. CLS operations are settled through a bank based in New York that employs a payment-versus-payment (PvP) protocol, in which a currency is delivered only if the other currency is also delivered. Thus, no exposure arises between banks trading in CLS because there is no settlement or Herstatt risk (i.e., the risk that a counterparty fails to perform at the time of settlement). Subsidiaries of international banks operating in Mexico are CLS members and settle their FX transactions in a secured manner. However, not all interbank FX operations are cleared through CLS, and in this case, large bilateral exposures may arise. Both FX receivable and payable transactions originate gross exposures between banks i and j. Finally, the current regulatory limit for interbank exposures is 100 percent of Tier 1 capital, a limit that applies solely to aggregate bilateral credit exposures such as loans, securities, and derivative positions. Our approach has the benefit of being based on actual interbank data and is comprehensive in that we cover 100 percent of the total assets of the Mexican banking sector.

3.1.3 Balance sheet data to measure bank standalone risk, competition, and bank-specific control variables

In Mexico, banks are requested each month to complete preset regulatory layouts, known as the "R01-Minimum Catalogue".[15] In these layouts, banks register all of their operations or trades related to their financial positions in standard balance sheet items such as assets, liabilities, and capital. The ultimate regulatory objective is to follow or monitor the financial

[14] However, when we analyze forward derivatives, we assume that contracts terminate at the time of failure. Therefore, the maximum loss considered for the failing bank's counterpart from derivatives is the favorable net amount due at the time of failure.

[15] See article 36 of Banxico's Law, which is publicly available at https://www.banxico.org.mx/regulations-and-supervision/legal-framework/banco-de-mexico-law/%5C%7B073CCF98-39BE-EC8F-E03E-6D4CFFC9FA1A%5C%7D.pdf; accessed on July 23, 2020.

health of each bank and the structure of its individual operations (i.e., any asset side operation, such as any loan, grant, buy or sell of securities or derivatives; or any liability side operation, such as receiving deposits, issuing debt, or any other operation related to any capital instrument) made with any counterparty independent of whether these are registered on the asset or liability side of the balance sheet. Each bank must ensure that the information content reflects financial operations up to the last day of the month. We refer the reader to Bátiz-Zuk and Lara-Sánchez (2022) for a detailed description of the timeline and process for the collection, validation, and supervisory penalties in the event that information is not available as prescribed in the regulatory framework. All information is publicly available, except for a single variable (i.e., employee remuneration).

Each bank must send data on an entity standalone basis without consolidating information with any of its foreign subsidiaries. In so doing, the information reflects all bank operations conducted in Mexico with either foreign or local counterparts. The bank's foreign subsidiaries complete on a standalone basis a different section within the same regulatory layout. The submitted information must be consistent with the accounting criteria predetermined by CNBV.[16]

3.1.4 Treatment of merger, consolidated, and macroeconomic data

In this paper, we use a consolidated bank's balance sheet data, which incorporate accounting information from banks along with that from their regulated multiple purpose financial companies (SOFOMES, its acronym in Spanish).[17] For the case of the consolidation between a bank and a SOFOME, we do not treat the consolidated entity as a new entity. Instead, we use the consolidated individual bank entity data that incorporate the accounting information of the SOFOME. In so doing, we refrain from including SOFOMES as standalone entities. Note that the Mexican banking sector has no consolidated data for large, internationally active banks.

[16] Note that any operation in the bank's foreign currency must be reported in local currency using as a conversion rate the exchange rate prescribed in local accounting guidelines.

[17] SOFOMES are intermediaries that originate any loan type but cannot take public deposits. SOFOMES could form part of a financial group or may be subsidiaries of bank entities. Their primary purpose is to perform operations such as leasing and factoring. Two types of SOFOMES exist: regulated and unregulated. In contrast to banks, SOFOMES are not allowed by law to raise funds from public deposits, which is why SOFOMES are also known as "non-deposit-taking and non-specialized loan institutions".

There are a number of mergers[18] that occurred during the period of our analysis. An issue of concern in any bank competition research is the treatment of mergers and acquisitions (see Claessens (1998), Jiménez et al. (2013), and de Ramon and Straughan (2020)). For any merger between any two banks, we follow the standard practice in the literature and include individual data for both entities until the date of the merger and only data for the merged entity afterward. Thus, we "create" a new entity and stop tracking information for the two individual bank entities. In this paper, we exclude banks with fewer than 24 months of data and those for which we found a consistency issue with the reported time series.[19,20] Overall, we have an unbalanced panel with 46 banks for the period from 2008Q1 to 2019Q1 (i.e., 45 quarters).

Regarding macroeconomic control variables, we use as a proxy for GDP the seasonally adjusted Global Indicator of Economic Activity (IGAE, its acronym in Spanish) and the inflation rate. The data source is publicly available at the National Institute of Statistics and Geography.

3.2 Methodology

To assess the effect of bank competition vis-à-vis systemic and standalone risk, we estimate a general regression model as follows:

$$SR_{i,t} = f(SR_{i,t-1}, C_{i,t}, Z_t, X_{i,t-2}), \tag{1}$$

where $SR_{i,t}$ is either a systemic or a standalone risk measure of bank i at time t (i.e., where t is measured using quarterly data), $C_{i,t}$ is a bank competition proxy measure, Z_t is a set of macroeconomic control variables, and $X_{i,t-2}$ are bank-level control variables and characteristics lagged by two quarters.

[18]Overall, we have two mergers in our sample (i.e., Banorte merged with IXE in April 2012, and Inbursa merged with Walmart in June 2015). The merger between Banorte and Interacciones in July 2018 was not considered, and we did not create a new entity because our data constraints to define variables require every bank to remain in operations for at least one year.

[19]In the empirical literature, that a few banks' regulatory reports suffer from inconsistent values is not strange. For example, Spierdijka and Zaourasa (2018, p.44) report bank-year inconsistent values for an annual sample of U.S. banks based on year-end regulatory Call Reports for 2000 to 2014.

[20]We did not consider the following banks in our analysis: ABC Capital, Bicentenario, Banco Wal-Mart, Consubanco, GE Money, ING Bank, Accendo Banco, and BiAfirme. During our sample period, the single bank that filed for bankruptcy was Bicentenario in mid-2014. This bank was very small and operated for a very short period (i.e., one year and three months).

We follow Jiménez et al. (2013) and use a dynamic panel model as a baseline to test whether there is a linear relationship between our systemic risk and competition proxy variable. In particular, we use the following equation to estimate our model:

$$SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}, \tag{2}$$

where α_i denotes bank fixed effects to control for unobservable bank individual heterogeneity that is constant over time, λ_t denotes calendar year dummy variables to control for time-varying business cycle conditions as well as for technological progress, and $\epsilon_{i,t}$ is the error term. We estimate our equations using the Arellano and Bond (1991) estimator in first differences, and we apply a two-step GMM approach with clustered standard errors by the bank to control for any pattern of heteroskedasticity and correlation within the banks. Further, the standard error calculations incorporate the Windmeijer (2005) finite sample correction.[21] We use a dynamic setting with a lagged dependent variable because our risk measures (i.e., systemic and standalone) have a significant degree of persistence. We expect that the lagged dependent variable has a significant positive coefficient. The average value of the first-order autocorrelation of our systemic risk measures ranges from 0.36 to 0.67. We instrument the lagged dependent variable and the competition measure using the second and third lags of systemic risk and competition measures.[22] In addition, we collapse the moment conditions to avoid endogenous variables' over-fit and instrument proliferation that could lead to unreliable instrument validity tests (see Roodman (2009b)). To test the validity of our estimations, we use the standard Hansen J test. Moreover, we verify that only first-order autocorrelation is observed in residuals and discard the presence of second-order autocorrelation (see Arellano and Bond (1991)).

In eq.(2), we use β to assess whether a linear association exists between systemic risk and competition at the bank level ($C_{i,t}$).[23] In particular, we focus on the sign, magnitude, and statistical significance of β.

As highlighted by Jiménez et al. (2013), it is not possible to estimate eq.(2) using ordinary least squares (OLS). Including a lagged dependent variable makes OLS estimation unreliable because the process of eliminating fixed effects creates a correlation between the regressors and the error term. Perhaps the greatest virtue of this model compared with any static alter-

[21] Without this correction, standard errors could be biased.
[22] Our estimations are robust to an alternative number (i.e., 3, 4, and 5) of lags as instruments.
[23] In unreported results, we estimate our model using a lagged competition variable.

native is that its design permits mitigation of a high degree of persistence in the dependent variable along with potential endogeneity sources. We can identify and describe at least three potential sources of endogeneity, namely, mild, moderate, and severe. According to Anginer et al. (2014, pp.14-15), a mild endogeneity concern may be generated between bank systemic risk and competition when omitting bank-level variables, such as bank ownership structure. As an example, it might be possible that bank shareholders determine limits on interbank exposures, or it could be that the risk appetite of each bank affects its interbank exposures. Moreover, the latter could have direct and/or indirect effects on a bank's market power. Following Anginer et al. (2014, pp.14-15), bank fixed effects are used to mitigate this type of endogeneity concern. Additionally, a moderate endogeneity concern may arise from contemporaneous feedback between bank characteristics with bank-level competition and risk indicators. Following Jiménez et al. (2013), to avoid this type of potential endogeneity, we use a two lag period (i.e., two quarters) for our bank control variables. Finally, note that our counterfactual risk measure shows improvement over the traditional standalone risk measures used in the literature for what we define as a severe endogeneity concern. Because bank-level competition and standalone risk metrics (e.g., Z-Score or non-performing loans) are based or depend on the profitability or performance measures, the possibility is high that there is a mechanic relationship and a feedback loop interaction between them. Using a counterfactual bank-level risk measure mitigates this source of concern because neither profitability nor performance is involved in the definition of our systemic risk measures.

3.3 Variable definition

In this section, we describe the definition of our main variables (i.e., systemic risk, standalone risk, and competition). Moreover, as a supplement to this section, Table A1 in Appendix A provides the definitions of the variables.

3.3.1 Dependent variables: Bank-level systemic risk measures

Our bank-level systemic risk measures are derived from empirical evidence on counterfactual simulation methods used in network theory to assess the impact of contagion in interbank markets.[24] Financial contagion in our indicators is limited to the interbank lending market, which is one of the most important risk channels through which shocks are propagated and amplified (Acemoglu et al., 2015). In essence, our measures incorporate the financial losses from contagions that arise essentially from direct interconnections. In this case, contagion occurs when a creditor bank does not have enough capital to absorb the financial loss that occurs as a consequence of the idiosyncratic initial default of any of its debtor bank counterparts. The seminal paper of Upper (2011) provides a comprehensive summary of the main findings, recent advances, and key modeling limitations.

We follow the algorithm originally applied to the Mexican banking sector by Guerrero-Gómez and Lopez-Gallo (2004). The structure of the interbank relationships and exposures[25] can be represented in matrix form as:

$$X = \begin{pmatrix} 0 & \dots & x_{1,j} & \dots & x_{1,N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \dots & 0 & \dots & x_{i,N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \dots & x_{N,j} & \dots & 0 \end{pmatrix} \quad \text{with } \sum_{j=1}^{N} x_{i,j} = a_i \text{ and } \sum_{i=1}^{N} x_{i,j} = l_j,$$

where X is an $N \times N$ matrix of bilateral interbank exposures, $x_{i,j}$ is the exposure of bank i vis-a-vis bank j such that a_i represents bank i's interbank assets and l_j represents bank j's interbank liabilities. The diagonal is full of zeros because banks do not lend to themselves. The aggregate bilateral interbank exposures $x_{i,j}$ represent the sum of gross bilateral current exposures in securities, derivatives, interbank operations, and FX between banks i and j. We populate the interbank matrix with reliable direct actual data on bilateral exposures. Empirical evidence exists that an interbank matrix based on actual bilateral exposures has several advantages over an interbank matrix based on ME (see Mistrulli (2011)). The main advantage of our method is that our estimates remain unbiased compared with those obtained from ME (see Upper (2011)). Moreover, ME cannot reproduce a number of stylized facts about interbank markets, such as its sparseness or tiering (see Upper (2011)). Tiering arises in interbank markets because lower-tier banks do not lend to each other; instead, transactions take place only with top-tier banks, which tend to be tightly linked (see Upper and Worms (2004) and

[24] Further, the patterns of interconnection between banks affect the amplification or attenuation of financial shocks (Allen and Gale, 2000, Freixas et al., 2000). Gai and Kapadia (2010) analyze how aggregate and idiosyncratic shocks influence contagion.

[25] Figure C1 in Appendix C illustrates the structure of the Mexican interbank exposure network at the end of any working day.

Craig and Von Peter (2014)).

The sequential default algorithm fully characterizes our contagion mechanism and can be described as a four-step process as follows: (i) we assume that bank k fails because of an unknown exogenous reason (i.e., because of an idiosyncratic shock); (ii) as a result, any bank j fails if it has a large bilateral exposure to bank k such that its regulatory capital ratio falls lower than the minimum 8 percent threshold; (iii) an additional round of contagion occurs when the aggregate exposure of any creditor bank to other banks that have failed in any previous round breaches its minimum 8 percent capital requirement; (iv) the contagion process stops when no new failure occurs in a specific round. This sequential default algorithm is in line with the current minimum capital requirement standard in the new Basel Accord.[26]

The capital adequacy ratio (CAR) of any bank i exposed to contagion risk can be calculated as:

$$CAR_i = \frac{RC_i - \sum_k \theta_{ik} x_{ik} \mathbb{1}_{k \in D}}{RWA_i - \sum_k \omega_{ik} \theta_{ik} x_{ik} \mathbb{1}_{k \in D}}, \tag{3}$$

where RC_i is the regulatory capital ratio for bank i (Tier 1 capital plus Tier 2 capital), θ_{ik} is the loss from a default of the interbank exposures of bank i to bank k, x_{ik} is the interbank exposure of bank i to bank k, $\mathbb{1}_k$ is an indicator variable that takes the value of 1 when bank k fails and zero otherwise, subscript D is a set that comprises all banks that have failed in any round, RWA_i is the bank's risk-weighted asset, and ω_{ik} is the regulatory risk weight of interbank exposures. A risk weight of 20 percent for banks is consistent with the Basel framework. We assume that θ_{ik} is constant across banks and rounds and takes a value of 100 in all cases. In this paper, bank failure occurs when a bank incurs losses that reduce its capital ratio to lower than 8 percent. However, we also follow an alternative and stricter default criterion and increase the minimum capital ratio requirement to 10.5 percent to stress test our model (i.e., this is consistent with Basel III minimum requirements).[27]

Our approach can best be explained as follows. We define a set of three systemic risk variables at the bank level: the ratio of total failed bank assets to the sum of bank assets; the interbank contagion loss as a percentage of regulatory capital; and the interbank contagion loss as a percentage of the sum of bank risk-weighted assets (RWAs).[28] For each of these three vari-

[26] Figure C2 in Appendix C illustrates how the contagion algorithm spreads through the interbank network structure.

[27] Appendix E describes the regulatory bankruptcy regime for the Mexican banking sector.

[28] At the bank level, we exclude in the numerator and in the denominator the size of the idiosyncratic bank failure related to total assets, regulatory capital, or risk-weighted assets.

ables, we compute the maximum value. To be consistent with the quarterly time frequency of our competition measures, we illustrate how we compute quarterly systemic risk measures from daily actual data as follows. The following example is based on the ratio of failed bank assets to the sum of bank assets, but the same principle applies to interbank contagion loss as a percentage of either regulatory capital or the sum of a bank's risk-weighted assets. For each quarter, we compute the daily ratio of failed bank assets to the sum of the assets at the bank level (i.e., the loss excluding idiosyncratic bank failure), which leads to approximately 60 point-in-time values for each bank. Then, we group the 60 daily values available in each quarter for each bank and compute a quarterly empirical distribution at the bank level. We use this distribution to compute the value of the maximum. However, other risk statistics (i.e., mean, VaR, and CVaR) could be computed. Figures A1 to A4 in Appendix A show the mean, median, and distribution of our systemic risk measures.

The sequential default algorithm used in this paper is similar in nature to that of Furfine (2003). This algorithm has been widely used in the Mexican empirical literature by several authors to analyze systemic risk. Canedo and Jaramillo (2009) propose a network model to analyze systemic risk in the banking sector and calculate the joint probability of bank failures using simulation methods. Martínez-Jaramillo et al. (2010) study a method to decompose the share of the loss distribution attributable to the initial shock from the contagion process and follow the evolution of several risk metrics, such as CVaR, for monitoring purposes. Solorzano-Margain et al. (2013) extend the network to analyze the role played by non-bank financial entities. Bátiz-Zuk et al. (2016) examine the role of imposing tighter limits on interbank exposures to reduce contagion and aggregate contagion losses. Moreover, when the banks' behavioral responses under a stricter regulatory lending regime are taken into account, they find that tighter limits for inter-DSIBs exposures are useful tools for reducing contagion risk.

The sequential default algorithm has three sources of criticism. First, this algorithm essentially solely investigates the direct mechanical contagion effect in the interbank market (see Memmel et al. (2012)). Thus, only part of all of the possible contagion effects is considered, and the creditor banks' potential reactions, such as the use of alternative reserves, are not considered. Second, the empirical evidence suggests that the contagion loss in the total banking sector depends to a significant extent on the loss given default (LGD) value (see Upper and Worms (2004), Furfine (2003), and van Lelyveld and Liedorp (2006)). It is well documented that LGD rates vary, which is not considered in this paper. We simplify our approach and take a very conservative view by fixing the LGD value to 1, which maximizes the risk of contagion.

In this regard, our approach assumes that the recovery process is essentially characterized by a significant degree of uncertainty. Finally, some empirical papers report that the loss in the banking sector is, in general, economically small (see Furfine (2003) and Karas et al. (2012)). However, as explained by Upper (2011), the cause of the small contagion effect detected is the lack of reliable (and comprehensive) actual data on bilateral interbank exposures between banks and other financial institutions. As shown by Bátiz-Zuk et al. (2016), this limitation can be overcome by using proprietary data from the Banco de México that include detailed, actual aggregated bilateral interbank exposures (i.e., both on- and off-balance sheet exposures) for all banks that form part of the system. Moreover, as in their study, our sample period covers the recent global financial crisis.

Our sequential default algorithm has at least two relevant benefits. First, it is comprehensive because it includes 100 percent of the total assets of the Mexican banking sector and is based on actual interbank data. Second, it is possible to obtain bank-level systemic risk measures irrespective of bank size, ownership (e.g., public or private), or business model (e.g., traditional or investment). Alternative measures proposed in the literature, such as the CoVaR (see Anginer et al. (2014) and Hirata and Ojima (2020)), SRISK (see Leroy and Lucotte (2017)), and MES (see Silva-Buston (2019)), require daily stock and foreign exchange market information. Unfortunately, the application of any of these measures in Mexico and other countries is very limited because many foreign bank subsidiaries are not public. As an example, in Mexico, five out of seven D-SIBs are foreign standalone bank subsidiaries that are not public and listed on the domestic stock market.

Conducting a reliable bank-level correlation analysis to assess whether our interbank contagion risk proxy correlates with other market-driven systemic risk indicators is difficult (e.g., CoVaR, MES, SRISK) when the data for this type of analysis is available for only one out of seven D-SIBs. Moreover, there is consensus that the heterogeneity among large banks is significant, especially on the asset side for which the composition of both on- and off-balance sheet items differs among banks. Additionally, a large body of literature investigates risk taking and other bank behavior differences between domestic and foreign banks. We have no way to properly investigate this issue because we have market data on only one domestic D-SIB and a few no-DSIBs listed on the Mexican stock exchange.

3.3.2 Dependent variables: Bank-level standalone risk measures

In this paper, we consider two popular bank-level standalone risk measures, namely, the non-performing loan (NPL) ratio and the Z-score. Both measures are based on accounting-based data and reflect the bank's risk-taking profile. These two indicators are useful to compare whether there is any difference with respect to their bank-specific systemic risk counterparts and have been widely used in the literature that investigates the relationship between competition and bank risk taking (see Jiménez et al. (2013) and Berger et al. (2009) and the references therein). The non-performing loan ratio (NPL_{it}) of bank i at time t is defined as:

$$NPL\ Ratio_{it} = \frac{NPL_{it}}{PL_{it} + NPL_{it}}, \tag{4}$$

where NPL_{it} is the bank's non-performing loan size and PL_{it} is the bank's performing loan size. A higher NPL ratio indicates an increase in the bank's failure risk attributable to a deterioration in the loan portfolio.[29] In turn, the Z-score (Z_{it}) measures a bank's book-value failure probability (i.e., bank's survival), which is defined as:

$$Z_{it} = \frac{ROA_{it} + C_{it}/A_{it}}{\sigma_{it}^{ROA}}, \tag{5}$$

where ROA_{it} is the return on assets of bank i at time t, C_{it} is the bank's total capital, A_{it} is the bank's total assets, and σ_{it}^{ROA} is the standard deviation of the bank's ROA, which is calculated using a two-year rolling window of annualized returns.[30] As highlighted by de Ramon et al. (2020), this is convenient to prevent variations in the level of the ROA and the capital ratio from becoming the single drivers of the Z-score variability. A greater Z-score value suggests that the bank's risk of insolvency is lower. A convention in this literature is using the logarithm of the Z-score to minimize either the presence of outliers or data skewness in the sample (Jiménez et al. (2013) and de Ramon et al. (2020)).[31]

[29]Panel A in Figure A5 in Appendix A shows the distribution of the bank-level NPL ratio.
[30]We have verified that the level of variation in the denominator of the Z-score is sufficient.
[31]Panel B, Figure A5 in Appendix A shows the evolution of the Z-score.

3.3.3 Explanatory variables: competition measures

There is consensus in the empirical literature that competition measures are not perfect substitutes because they each have advantages and limitations. Thus, studies should consider as many measures as possible because each incorporates a different feature of competition. In this paper, we use as our main competition measures the bank-level Lerner index. In addition, for robustness purposes, we use other competition measures, such as the asset-weighted and unweighted aggregate Lerner indices at the sector level and the Boone indicator (see Appendix D). We also use two structural competition measures for robustness purposes: the Herfindahl-Hirschman index (HHI) and a bank's market share as measured by its asset size.

3.3.3.1 Lerner index

The Lerner index (Lerner, 1934) is designed to measure the market power of any bank at any time by quantifying the difference between the bank's price and its marginal cost. Under the assumption of perfect competition, the price and its cost should be equal, and a positive gap will appear as the market becomes less competitive. Greater bank monopoly or market power is inferred when the value of the Lerner index differs from zero. An advantage of the Lerner index over other non-structural competition measures is that it yields an individual bank measure of market power (Degryse et al., 2009). Moreover, Anginer et al. (2014) considers the Lerner index as the primary measure of competition because of the following advantages over other metrics: (i) it is the best for capturing the concept of bank franchise value (see Beck et al. (2013)); (ii) it is more comprehensive because it captures the pricing power of both sides of the balance sheet (i.e., a bank's asset and funding sides) (see Anginer et al. (2014)); (iii) it does not rely on precise definitions of the geographic product market (see Aghion et al. (2005); and (iv) it is available for the bank level. The Lerner index is defined as:

$$L_{it} = \frac{P_{it} - MC_{it}}{P_{it}}, \tag{6}$$

where L_{it} is the Lerner index of bank i at time t, P_{it} is the bank's output price, and MC_{it} is its corresponding marginal cost. Following the literature, we use as a proxy for P_{it} the bank's total interest and non-interest revenue per output unit, and we use the bank's total assets as a proxy for the bank's output.

To estimate the bank-level Lerner index, we rely on an approach that is fully described in

Bátiz-Zuk and Lara-Sánchez (2022). This approach is based on estimating marginal costs from the parameters of a translog single output-cost function with bank and time fixed effects (see also Berger et al. (2009), Beck et al. (2013) and de Ramon and Straughan (2020)).

3.3.3.2 Estimation of bank-level Lerner index

The bank-level Lerner index is estimated using the following translog total cost function, which is defined as:

$$\begin{aligned} log(C_{it}) = \quad & \alpha_i + \eta_t + \beta_1 log(Q_{it}) + \beta_2 log(Q_{it})^2 + \sum_{k=1}^{3} \gamma_k log(W_{it}^{(k)}) + \\ & \sum_{k=1}^{3} \phi_k log(Q_{it}) log(W_{it}^{(k)}) + \sum_{k=1}^{3}\sum_{j=1}^{3} \delta_{kj} log(W_{it}^{(k)}) log(W_{it}^{(j)}) + \epsilon_{it}, \end{aligned} \tag{7}$$

where C_{it} is the total cost for bank i at time t and α_i and η_t are parameters to control for both bank and time fixed effects [32], respectively, Q_{it} is the bank's total asset (i.e., proxy for output); $W_{it}^{(1)}$, $W_{it}^{(2)}$, and $W_{it}^{(3)}$ are interest, labor, and fixed expense (i.e., operational costs) input prices for which we use the ratios of interest expense, labor expense, and operational expense to total assets as proxies. Additionally, we include a set of constraints[33] for the input price coefficients to ensure that the linear cost function is homogeneous of degree one. Specifically, we use a constrained least squares panel regression technique with clustered standard errors at the bank level. Finally, to calculate the marginal cost, we differentiate eq.(7) and use the estimated parameters as follows:

$$MC_{it} = \frac{C_{it}}{Q_{it}} \left(\beta_1 + 2\beta_2 + \sum_{k=1}^{3} \phi_k log(W_{it}^{(k)}) \right). \tag{8}$$

This time varying bank-specific measure allows researchers to compare the individual market power between banks.[34]

[32] Bank fixed effects are used to control for bank heterogeneity. In turn, time fixed effects are used to control for business cycle variations and technological progress. This approach was originally introduced by Berger et al. (2009) and subsequently used by Beck et al. (2013).

[33] The three coefficient constraints are i) $\sum_{k=1}^{3} \gamma_k = 1$, ii) $\sum_{k=1}^{3} \phi_k = 0$, and

iii) for all k, $\sum_{j=1}^{3} \delta_{kj} = 0$.

[34] Figure A6 in Appendix A shows the evolution of the distribution of the bank-level Lerner index.

3.3.3.3 Unweighted and asset-weighted aggregate sector-level Lerner index

In our robustness test, we use two aggregate sector-level competition measures. In particular, the unweighted and asset-weighted aggregate sector-level Lerner indices (i.e., $L_{u,t}$,$L_{w,t}$) for the banking sector of any country at any period t can be computed as follows:

$$L_{u,t} = \sum_{i=1}^{n} L_{i,t}/n \tag{9}$$

$$L_{w,t} = \sum_{i=1}^{n} \omega_i L_{i,t}, \tag{10}$$

where $L_{i,t}$ is the individual or bank-level Lerner index of bank i at time t, as defined in eq.(6), and ω_i is the bank's market share. It is possible to use the bank's total asset, deposit, or loan portfolio to private non-financial entities as a weighting factor. We could also use an unweighted Lerner index for which all banks have the same relative importance, and this equals $1/N$. A time-varying asset-weighted version of the Lerner index is preferred in our context because it assigns more weight to large banks. The downside of this variable is that it is not an individual bank measure, so bank heterogeneity may be lost. However, using this indicator makes it possible to assess the relationship between an increase in the weighted average of the banking sector's market power.

3.3.4 Explanatory variables: Bank-level characteristics and macro controls

The choice of bank-level controls is based on the literature exploring the factors that determine bank failure (e.g., Cole and White (2012)) and other studies investigating the relationship between risk and competition (e.g., Jiménez et al. (2013) and de Ramon et al. (2020)). Bank size is relevant because large banks enjoy benefits, such as better diversification across countries, using different assets. We use the log of total assets as a proxy for bank size. To control for a bank's business model diversification, we use the ratio of loans to non-financial private entities and households to assets. In addition, we consider the retail funding ratio as a proxy for a bank's liquidity risk. Moreover, as a proxy for the asset quality and credit risk profile, we use the ratio of loan loss provisions to assets. The expected credit risk increases with greater values of this ratio. Finally, we also use the bank's regulatory capital adequacy ratio (CAR) and the average risk weight as a proxy for the bank's risk-taking profile (i.e., unexpected loss) and capital absorption capacity.

Following Jiménez et al. (2013), developing a clear expectation for bank characteristics is difficult because business models and the banks' risk-taking profiles vary widely. The underlying reason is that it is difficult to control for loan quality when analyzing individual bank ratios, such as the loan-to-assets ratio. Banks with good origination standards (i.e., selection, screening, and monitoring of customers) and adequate risk management should have a lower risk, supporting the view of a significant negative coefficient. However, banks with higher loan growth rates and rising loan-to-assets ratios may relax their lending standards during expansion periods, implying a positive significant coefficient. We expect a positive coefficient between bank size and systemic risk because large D-SIBs banks represent a higher source of systemic risk.

Following de Ramon et al. (2018), we control for macroeconomic conditions by introducing the current and lagged values of the year-on-year (YoY) real GDP growth rate and the annualized current inflation rate because we expect that economic activity influences interbank activity and bank borrowers' loan payment capacity, ultimately influencing a bank's standalone and systemic risk measures. Naturally, we expect a significant negative coefficient for the economic activity and the inflation rate variables.

4 Results

4.1 Summary statistics

In this section, we describe our empirical results. In our sample, Table 1 shows the composition of the Mexican banking sector at the bank level. Columns (1) to (3) of Table 1 show the minimum, average, and maximum values of the bank's market share based on total assets. The size of the bank's market share differs markedly depending on whether the bank is a D-SIB. The largest D-SIB (i.e., BBVA Bancomer) has a maximum share value of 26.82 percent, whereas the smallest D-SIB (i.e., Inbursa) has a maximum market share value of 2.56 percent. Table 1 also shows that the two largest non-D-SIBs (i.e., Deutsche Bank and Interacciones) have maximum market share values of 4.92 and 2.55 percent, respectively. The results of this analysis suggest that using market share as a weighting factor for the aggregate Lerner index leads to an indicator that largely reflects the market power and relative importance of systemic banks in the banking sector.

Overall, we have 46 banks in our sample. Column (4) of Table 1 shows that 16 out of the 46 banks in our sample are foreign bank subsidiaries. Column (5) of Table 1 shows that out of the 46 banks, there are nine D-SIBs[35]. A closer inspection shows that five out of the nine D-SIBs are foreign bank subsidiaries. Column (6) of Table 1 shows the bank's entry status. Our sample is initiated with 32 banks (e.g., Entry=1). During our sample period, 12 banks entered after 2008:Q1 and received a bank license to operate in the banking sector (e.g., Entry=2), whereas two banks are virtually created as a result of a merger with two small banks (e.g., Entry=3). Column (7) of Table 1 shows that 41 banks remained in operation during our sample period (e.g., Exit=1), whereas four banks exited as a result of two mergers (e.g., Exit=2). During our sample period, only one bank (i.e., Deutsche Bank) ceased operations (e.g., Exit=3) as a result of a restructuring of the holding company.

Figure 1 shows the evolution of two bank-level systemic risk measures (i.e., maximum quarterly value of both the maximum of each bank-level failed bank assets and the maximum of each bank-level interbank contagion loss to regulatory capital, two bank-level standalone risk indicators (i.e., Z-score and NPL ratio), and two aggregate Lerner indices at the banking sector level (i.e., unweighted and asset-weighted aggregate Lerner index). Panel A shows the evolution of the maximum value of failed bank assets to the sum of assets at the bank level, whereas Panel B shows the evolution of the maximum value of interbank contagion loss to regulatory capital at the bank level for the Mexican banking sector. Panels C and D show the evolution of the average Z-score and non-performing loan ratio (NPL), respectively.

There seems to be a different pattern among the two bank-level systemic risk measures. The maximum of failed bank assets to the sum of assets (MFBASA) has a similar volatility as the maximum of interbank contagion loss to regulatory capital (MICLRC) during the global financial crisis (GFC) period (i.e., 2008-2010). After the GFC, MICLRC had three spikes (i.e., 2014:Q4, 2016:Q3, and 2019:Q4), more volatility, and an uptrend, whereas MFBASA had one spike (i.e., 2015:Q4), less volatility, and no trend. In contrast, the evolution of the two standalone risk indicators in Panels C and D differ significantly compared with that of any of the two systemic risk measures. The Z-score has an overall upward trend, suggesting

[35]Two of the nine D-SIBs in the Table correspond to D-SIBS that were virtually created as a result of a merger during our sample period.

Table 1: Banks in Mexico: Market share, ownership, D-SIB, and entry/exit status

Bank	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Market share			Ownership	D-SIB	Entry	Exit
	Min	Avg	Max			(1,2,3)	(1,2,3)
BBVA BANCOMER	19.71	22.08	26.82	BBVA (Spain)	✓	1	1
CITIBANAMEX	12.71	17.26	23.29	Citigroup (USA)	✓	1	1
SANTANDER	11.52	13.99	17.59	Banco Santander (Spain)	✓	1	1
BANORTE	9.85	10.81	12.34		✓	1	2
BANORTE MERGED	9.78	11.71	13.35		✓	3	1
HSBC	6.98	8.22	10.67	HSBC (UK)	✓	1	1
INBURSA MERGED	3.94	4.40	4.77		✓	3	1
SCOTIABANK	2.98	4.02	5.74	Scotiabank (Canada)	✓	1	1
INBURSA	2.56	3.89	4.88		✓	1	2
BANCO DEL BAJÍO	1.29	1.79	2.41			1	1
BANCO AZTECA	1.15	1.45	1.86			1	1
BANREGIO	0.66	1.09	1.43			1	1
IXE	0.62	1.35	2.42			1	2
INTERACCIONES	0.61	1.65	2.55			1	2
J.P. MORGAN	0.39	0.85	1.67	JP Morgan Chase & Co (USA)		1	1
AFIRME	0.34	1.30	1.86			1	1
BANK OF AMERICA	0.33	1.08	2.16	Bank of America Corporation (USA)		1	1
BANCA MIFEL	0.30	0.62	0.82			1	1
INVEX	0.23	0.72	1.27			1	1
AMERICAN EXPRESS	0.17	0.26	0.42	American Express Company (USA)		1	1
VE POR MÁS	0.14	0.36	0.67			1	1
CREDIT SUISSE	0.13	0.42	0.97	Credit Suisse Grouo (Switzerland)		1	1
BARCLAYS	0.13	0.56	1.67	Barclays (UK)		1	1
BANSÍ	0.12	0.27	0.43			1	1
BANCO BASE	0.09	0.23	0.38			2	1
COMPARTAMOS	0.08	0.25	0.37			1	1
MUFG BANK	0.06	0.21	0.42	MUFG Bank Ltd. (Japan)		1	1
INMOBILIARIO MEXICANO	0.06	0.07	0.08			2	1
CIBANCO	0.04	0.33	0.62			2	1
FINTERRA	0.03	0.04	0.05			2	1
MIZUHO BANK	0.03	0.05	0.08	Mizuho Financial Group (Japan)		2	1
DEUTSCHE BANK	0.02	1.33	4.92	Deutsche Bank AG (Germany)		1	3
MONEX	0.02	0.64	1.22			1	1
BANCREA	0.02	0.09	0.15			2	1
SABADELL	0.01	0.24	0.72	Banco Sabadell Group (Spain)		2	1
MULTIVA	0.01	0.60	1.22			1	1
AUTOFIN	0.01	0.05	0.08			1	1
VOLKSWAGEN BANK	0.01	0.06	0.09	Volkswagen Group (Germany)		2	1
ACTINVER	0.01	0.18	0.40			1	1
BANCO AHORRO FAMSA	0.01	0.22	0.40			1	1
INTERCAM BANCO	0.01	0.17	0.32			1	1
BANCOPPEL	0.01	0.32	0.72			1	1
ICBC	0.01	0.04	0.06	ICBC (China)		2	1
FORJADORES	0.01	0.01	0.01			2	1
DONDÉ BANCO	0.00	0.01	0.01			2	1
BANKAOOL	0.00	0.02	0.04			2	1

Notes: This Table presents a bank's market share based on total assets along with ownership type, D-SIB status, and bank entry or exit conditions. Statistics are based on data from 2008:Q1 to 2019:Q1. Columns (1) to (3) show values for the minimum, the average, and the maximum of a bank's market share during the sample period. Column (4) shows the bank's ownership and identifies whether the bank is a Mexican subsidiary owned by an international or foreign financial group. Column (5) identifies whether the bank is a Mexican D-SIB. Column (6) is a categorical variable that takes one of three values. It takes the value one when the bank forms part of our study from the beginning of the sample (i.e., 2008:Q1), it takes the value two if the bank entered our sample at any point after 2008:Q1 (deferred entry), and it takes the value of 3 if the bank is created as a result of a merger or an acquisition. Column (7) is a categorical variable that also takes one of three values. It takes the value of one when the bank operated at all points available in our sample period, it takes the value of two if the bank merged during our sample period, and it takes the value of three if the bank ceased operations at any point during our sample period. Banks are ordered according to the minimum value of their market share.

that the average individual bank risk decreased during our sample period. The NPL ratio increased from 2008 to mid-2010 and then decreased until early 2013. Between 2013 and 2014, there was a spike that is attributed to an increase in impaired loans in the construction sector (see Iakova et al. (2014)), and then it trended downward at a slow rate of decay.

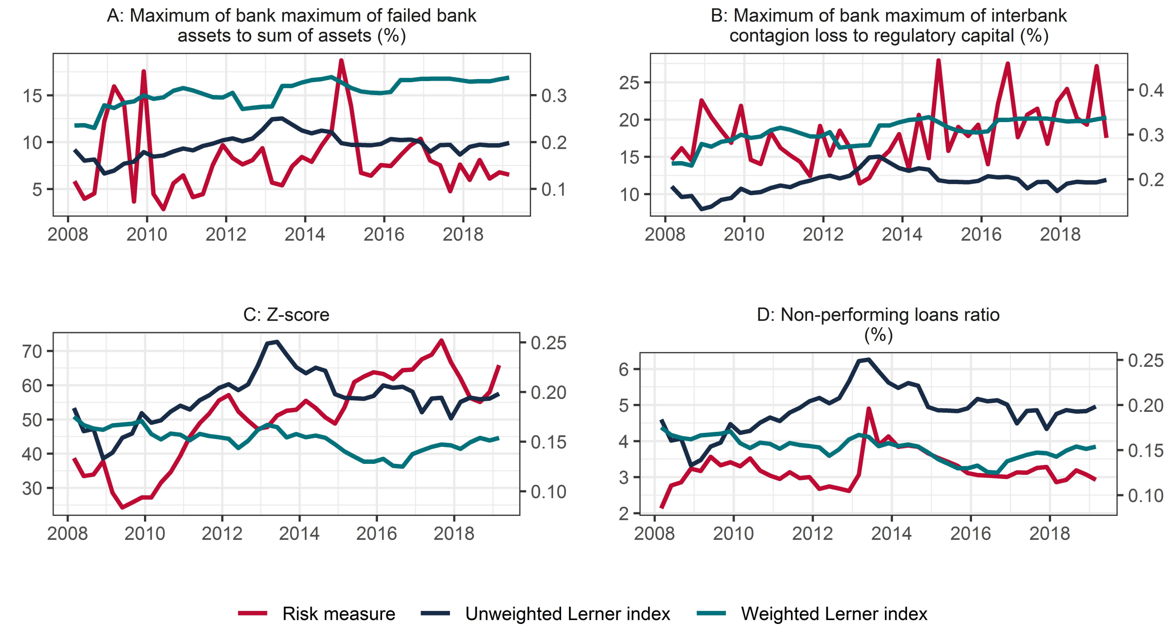
Additionally, the pattern differs between the two sector-level competition measures, especially during the second half of the sample period, where the two Lerner indices move in opposite directions exactly when there is a huge spike in the NPL ratio. We identify three periods based on changes in the trend of the aggregate unweighted Lerner index. First, during the financial crisis between 2008 and 2009, market power decreased. Second, from 2009 to 2013, market power increased and reached its global peak in 2013. Finally, market power exhibited a downward trend (i.e., albeit the rate of decay varied during this period) from mid-2013 to 2019, suggesting that competition improved. Overall, it is difficult to identify with this indicator whether competition intensity improved during the sample period. In contrast, the weighted aggregate Lerner index has an overall upward trend, suggesting that the weighted average market power of large banks in the banking sector increased during our sample period. As expected, the weighted aggregate Lerner index has a higher level than the unweighted aggregate Lerner index because of the stronger market power that characterizes large banks. As documented in Bátiz-Zuk and Lara-Sánchez (2022), there is significant heterogeneity in the evolution of bank-level Lerner indices.

We summarize our findings based on Figure 1 as follows: (i) the nature and evolution between the bank-level systemic and standalone risk indicators differs; (ii) it is difficult to identify whether a relationship exists between competition and the two bank-level systemic risk indicators, suggesting that other tail risk indicators should be considered;[36] (iii) there seems to be a positive (mixed) relationship between the Z-score (NPL ratio) and the weighted aggregate Lerner index; (iv) there seems to be a mixed relationship between the Z-score (NPL ratio) with the unweighted Lerner index because it is positive (negative) for the first half of the sample period but then seems to turn negative (positive) as the unweighted Lerner index decreases.

Table 2 presents the summary statistics of the variables used in our study. The total number of bank-level observations after applying filtering rules as described in section 3 is 1,630. The panel is unbalanced and includes 46 banks and 45 points in time or quarters. As expected, the

[36]Figure A7 shows the evolution at the bank level of the average and maximum of the worst contagion chains of failed bank assets to the sum of total assets and interbank loss to regulatory capital.

Figure 1: Evolution of bank-level systemic risk measures and competition over time: 2008Q1-2019Q1.



Source: Banco de México, authors' calculations. **Notes**: This figure shows the quarterly evolution of the worst contagion chain of our bank-level systemic and standalone risk indicators and the unweighted and weighted aggregate Lerner indices for the period 2008:Q1 to 2019:Q1. All bank-level risk variables are measured on the left vertical axis and identified with a solid red line. In turn, both competition proxies are measured on the right axis, and a dark and a light blue solid line are used to identify the unweighted and weighted aggregate Lerner index, respectively. The labels on the horizontal axis indicate the end of the year. Panel A shows the evolution of the maximum of failed bank assets to the sum of assets. Panel B shows the evolution of the maximum of the interbank contagion loss to regulatory capital. Bank systemic risk and the standalone variables are defined in section 3.3.1 and 3.3.2, respectively. The two competition measures are defined in section 3.3.3.

mean value for our systemic risk measures increases as the risk statistic becomes more conservative (i.e., VaR (95%), E.S. (95%), Maximum)). Additionally, as expected, the size of the interbank contagion loss is higher when we use in the denominator regulatory capital instead of banking sector RWAs. Interestingly, the range of values of the primary bank-level systemic risk measures varies widely because of the significant heterogeneity among them. The minimum value is zero because there are periods in which a bank failure may be insufficient to trigger a direct contagion. This insufficiency may occur especially for small idiosyncratic banks' failures from their low or non-existent degrees of interconnection (i.e., bilateral exposure size) with other banks. Additionally, the median value is consistently smaller than the mean value because of the heavy-tail nature of any loss distribution. It is convenient to point out that a large difference exists in the magnitude between the maximum and the 75th percentile value for all systemic risk variables. Systemic risk analysis in network theory is particularly designed to address the most extreme adverse event that may arise from the worst contagion chain.

Undoubtedly, in the literature, the primary variables related to the worst contagion chain are the most interesting. In this regard, Table 2 shows that for the ratio of failed bank assets to the sum of total assets, the maximum value that originates from the worst contagion chain is 18.72 percent. In fact, this value is comparable to that reported in Upper (2011, pp.118-120), even though the structure of the banking sector, the methodologies, and the data differ across countries.[37] In turn, the maximum interbank contagion loss to regulatory capital (RWAs) is 27.94 percent (4.41 percent). In other words, this statistic implies that the worst contagion chain may lead to a severe decrease—equivalent to 4.41 percent of the system-wide capital adequacy ratio. In the literature, it is difficult to find reference statistics for the interbank contagion loss resulting from a contagion because this measure is not as popular or as traditional as the share of affected assets.

Regarding our secondary systemic risk measures, the average NBF value suggests that less than one bank fails on average (i.e., 0.65) as a consequence of idiosyncratic bank failure but that up to almost 8 banks may fail in the worst contagion chain. In turn, the average of the SBF suggests that the number of times that a specific bank fails as a consequence of any other idiosyncratic bank failure (SBF) is small on average (i.e., 0.37) but may increase to more than 7 in the worst contagion chain.

Table 2 shows that the two standalone risk measures (i.e., $Z-Score$ & NPL ratio) suggest that significant heterogeneity exists in a bank's business model. Interestingly, the values reported for the Mexican banking sector in Table 2 are similar to those reported in the literature for other banking sectors in advanced economies. This comparison is relevant because the size and structure of the Mexican banking sector is small compared with those of the United Kingdom or any other industrialized country that is a member of G7.[38] Interestingly, both measures seem asymmetrically distributed. For example, the Z-score range goes from 0.33

[37] The share of total assets that is destroyed by contagious defaults (i.e., excluding the trigger bank) is 20 percent of the total assets for Belgium (see Degryse et al. (2007)); 16 percent for Italy (see Mistrulli (2005)); 16 percent for the UK (see Wells (2004)); and 15 percent for Germany (see Upper and Worms (2004)). Although these values may be regarded as small, Bátiz-Zuk et al. (2016) show that the share of affected assets may increase up to 44 percent in stress test conditions.

[38] For the bank-level Z-score, see de Ramon et al. (2020) for a sample of UK deposit-taking entities and Berger et al. (2009) for a sample of international banks. In particular, the Z-score mean (standard deviation) reported for Mexico is 50.83 (44.74), whereas it is 51.38 (45.37) for the United Kingdom (see de Ramon et al. (2020)). For a sample of 23 industrialized countries, it is 56.76 (48.86) (see Berger et al. (2009)). For the bank-level non-performing loans ratio, see Jiménez et al. (2013, p.189). In particular, the NPL mean (standard deviation) value reported for Mexico is 3.26 percent (5.18 percent), whereas for Spain, 4.44 percent (4.93 percent).

to 328.57. An average bank in the sample has a Z-score value of 50, whereas the median bank has a Z-score value of 37. Additionally, this single risk variable has a standard deviation that is lower than its mean. In our estimations, we use the logarithm of the Z-score to mitigate the presence of outliers and the highly skewed nature of the data in our sample. In turn, the NPL ratio range is from 0 to 31.67 percent. An average (median) bank in the sample has a NPL ratio value of 3.26 percent (2.09 percent), with a large degree of variability observed across banks (5.18 percent) as measured by the standard deviation. In our estimations, we follow Jiménez et al. (2013) and use the log-odds transformation of a bank's NPL ratio, which changes the variable's support from the unit interval to the real number line.

Regarding our competition indicators, we report in Table 2 both the bank-level Lerner index and its asset-weighted and unweighted aggregate version for the banking sector. The value for both measures is consistent with other values reported in the literature.[39] In contrast to the bank-level systemic and NPL risk variables, these two competition measures report standard deviations that are smaller than their mean values. Moreover, these variables do not have a skewed nature, as evidenced by the fact that their mean and median values are almost the same. An average bank in the sample has a bank-level Lerner index value of 0.20, whereas the median value is 0.20. These values are significantly lower than the value of 0.31 reported for the mean and median of the weighted aggregate Lerner index. This result is expected because large banks have greater individual market power (i.e., higher bank-level Lerner index). Table 1 shows that the market value of large banks is significantly higher than that of small banks. For completeness, we also include other competition measures used for robustness purposes.

In our sample, an average bank has total assets of 168 bn (pesos), the share of private loans to total assets is 0.38, the retail funding ratio is 0.49, the provision ratio is 0.02, the capital adequacy ratio is 23 percent, and the average risk weight is 0.62. As expected, the standard deviation of the unexpected loss performance measure (i.e., the capital adequacy ratio with the standard deviation of 27.34 percent) is greater than that of its expected counterpart (i.e., the provisions to asset ratio with a standard deviation of 3 percent) because there is greater

[39]The value of the average and median (e.g., both values are 0.20) of the bank-level Lerner index and the range of values of the unweighted aggregate Lerner's, which vary between 0.13 and 0.25, are in line with those reported in the literature for these indicators in advanced economy banking sectors. For example, see de Ramon and Straughan (2020, p.10) for a sample of UK banks, Berger et al. (2009, p.109), Beck et al. (2013, pp.241-242), and Anginer et al. (2014) for a sample of international banks, Buch et al. (2013, p.1411) for a sample of German banks, and Maudos and De Guevara (2007, p.2113) for a sample of European banks. Moreover, our results are similar to those of a few Asian countries (e.g., South Korea, Hong Kong, and Taiwan) reported by Soedarmono et al. (2011) for a sample of 12 Asian banks.

uncertainty associated with determining the adequacy of the former.

Regarding our macroeconomic control variables, the global indicator of economic activity suggests that the Mexican economy expanded at an average annual rate of 2 percent during our sample period. In turn, the annual inflation rate is a one-digit number that has varied from 2.27 percent to 6.59 percent, with a mean value of 4.21 percent. The inflation rate is used as a control for periods of economic uncertainty related to higher price variations than expected.

Table A2 in Appendix A shows the correlation between our two risks (i.e., systemic and solvency) and the competition measures.[40] The pairwise correlation between our twelve primary bank-level systemic risk measures and the bank-level Lerner index is overall positive and significant at the 1 percent level. However, the size of the coefficient is not large and ranges from 0.25 to 0.34, suggesting that the strength of the linear correlation is moderate. Regarding our secondary bank-level systemic risk measures, the pairwise correlation is positive and significant for NBF but negative and significant for SBF. In any case, both are weakly associated when we consider their coefficient size. In turn, the standalone risk measures and the bank-level Lerner index have a significant positive (negative) correlation in the case of the Z-score (NPL ratio). These signs are consistent and expected because a higher (lower) value of the Z-score (NPL ratio) implies less risk. Regarding the pairwise correlation between our twelve primary bank-level systemic risk measures and the weighted aggregate Lerner index at the banking sector, we report that none of the variable coefficients are statistically significant, except for the average of the interbank contagion loss to RWAs, which is weakly significant at the 10 percent level. This result also applies to the secondary bank-level systemic risk measures. In contrast, both bank-level standalone risk measures seem correlated, but the strength and significance vary. The value of the Z-score coefficient is 0.18, which can be regarded as moderate and highly significant at the 1 percent level. The value of the NPL ratio coefficient is 0.04, which can be regarded as small and weakly significant at the 10 percent level. This simple correlation analysis is far from being conclusive because it is not possible to identify whether the relationship is nonlinear and significant.[41]

[40] Table A3 shows the correlation matrix of our independent variables (i.e., competition measures, bank characteristics and macro control variables).

[41] Figure A8 in Appendix A shows a scatter diagram to explore the nature of the empirical relation between two of our primary systemic risk measures and standalone measures (y-axis) and the bank-level Lerner index (x-axis), whereas Figure A9 shows the scatter diagram for the remaining bank-level systemic risk and competition variables.

Table 2: Summary statistics

Variable	Mean	Std Dev	Min.	Q. 25	Median	Q. 75	Max
Dependent variables							
Primary systemic risk/stability measures							
Avg. failed bank assets to sum of total assets (%)	0.23	0.69	0.00	0.00	0.00	0.05	5.84
VaR (95%) failed bank assets to sum of total assets (%)	0.54	1.44	0.00	0.00	0.00	0.23	14.31
E.S (95%) failed bank assets to sum of total assets (%)	0.63	1.62	0.00	0.00	0.00	0.27	16.72
Maximum failed bank assets to sum of total assets (%)	0.84	1.97	0.00	0.00	0.00	0.67	18.72
Avg. interbank loss to regulatory capital (%)	1.01	2.10	0.00	0.04	0.18	0.84	14.76
VaR (95%) interbank loss to regulatory capital (%)	1.68	3.33	0.00	0.07	0.30	1.44	25.49
E.S. (95%) interbank loss to regulatory capital (%)	1.89	3.64	0.00	0.09	0.35	1.73	26.09
Maximum interbank loss to regulatory capital (%)	2.18	4.11	0.00	0.11	0.42	2.19	27.94
Avg. interbank loss to RWAs (%)	0.16	0.34	0.00	0.01	0.03	0.13	2.45
VaR (95%) interbank loss to RWAs (%)	0.27	0.54	0.00	0.01	0.05	0.23	4.07
E.S. (95%) interbank loss to RWAs (%)	0.30	0.59	0.00	0.01	0.06	0.28	4.17
Maximum interbank loss to RWAs (%)	0.35	0.66	0.00	0.02	0.07	0.35	4.41
Secondary systemic risk/stability measures							
Avg. interbank NBF	0.65	1.08	0.00	0.00	0.00	1.00	7.89
Avg. interbank SBF	0.37	0.81	0.00	0.00	0.00	0.33	7.32
Individual risk/stability measures							
Z-score	50.83	44.74	0.33	20.04	37.81	68.07	328.57
Non-performing loan ratio (%)	3.26	5.18	0.00	0.92	2.09	3.49	31.67
Explanatory variables							
Competition measures							
Bank-level Lerner index	0.20	0.17	-0.71	0.11	0.20	0.31	0.70
Asset-weighted aggregate Lerner index*	0.31	0.03	0.23	0.30	0.31	0.33	0.34
Unweighted aggregate Lerner index*	0.19	0.02	0.13	0.18	0.19	0.21	0.25
Boone indicator*	-0.08	0.02	-0.14	-0.10	-0.08	-0.07	-0.04
HHI based on bank's total assets*	1277.50	136.31	1130.11	1174.62	1210.00	1444.07	1552.76
Market share based on total assets* (%)	2.71	5.22	0.00	0.23	0.56	1.56	26.48
Bank-level controls							
Bank size (total assets)[1]	168.39	332.75	0.34	13.20	32.24	110.88	2035.34
Loans to non-financial private sector to assets	0.38	0.26	0.00	0.16	0.36	0.58	0.94
Retail funding to total liabilities	0.49	0.28	0.00	0.26	0.52	0.70	0.99
Provision to assets ratio	0.02	0.03	0.00	0.01	0.01	0.03	0.17
Capital adequacy ratio (%)	23.08	27.34	10.46	14.31	16.29	20.59	463.08
Average risk weight	0.62	0.28	0.05	0.41	0.59	0.77	1.77
Macroeconomic controls							
Global indicator of economic activity (YoY %)	1.99	2.55	-7.92	1.60	2.43	3.24	6.75
Inflation (%)	4.21	1.08	2.27	3.46	4.10	4.91	6.59

Notes: This Table presents summary statistics for the dependent and independent variables used in the baseline estimations and robustness tests in which we analyze the link between bank-level risk and competition measures. All variables are defined in section 3.3. The data cover the period from March 2008 to March 2019 at a quarterly frequency. Capital refers to a bank's regulatory capital (i.e., tier 1 plus tier 2). NBF refers to the number of banks that fail as a consequence of each idiosyncratic bank failure, whereas SBF refers to the number of times that a specific bank fails as a consequence any other idiosyncratic bank failure, as defined in section 3.3. Our panel is unbalanced and includes 46 banks observed during 45 quarters. The total size of the sample available for estimation purposes is 1,630. In our sample period, two small banks exited as a result of mergers. Initially, we start with 32 banks in the first period; a total of 12 banks received a license to operate after this period, and two new bank entities were created as a result of two mergers.

[1] Total assets units are in thousands of millions of Mexican pesos. The definition for U.S. billions differs from the one used in Mexico. In the United States, a billion equals a thousand million (i.e., 1,000,000,000), whereas in Mexico, a billion is equal to a million million (i.e., 1,000,000,000,000).

*This Table includes variables used in our robustness test for completeness purposes.

4.2 Baseline results

4.2.1 Systemic-risk-competition nexus

In this section, we examine whether bank competition is linearly related to systemic risk after controlling for bank characteristics and macroeconomic conditions. For our baseline analysis, we estimate the regression specification as described in eq.(2), section 3.2. The three bank-level systemic risk dependent variables[42] are defined in section 3.3.1, and the standalone risk variables are described in section 3.3.2. Our main explanatory variable of interest is bank competition as measured by the bank-level Lerner index, which is defined in section 3.3.3. All explanatory control variables are defined in section 3.2.

Table 3 presents the coefficient estimates for our baseline model. We want to assess what happens when only the lagged dependent variable and the bank-level Lerner index are included as explanatory variables because a few of our control variables are correlated with each other. Hence, we analyze eq.(2) including and excluding the control variables. Columns (1), (3), and (5) in Table 3 show the estimates when excluding bank characteristic and macroeconomic control variables. We find that the relationship between the bank-level Lerner index and the systemic risk variable is both negative and statistically significant at least at the 5 percent level for our three specifications. The coefficient estimate for the maximum of failed bank assets to sum of total assets, which is the most popular systemic risk variable, suggests that a one standard deviation increase in market power (i.e., a 0.17 unit increase in the bank-level Lerner index) is associated with a 0.92 standard deviation reduction in systemic risk.[43] Columns (2), (4), and (6) in Table 3 show the estimates when including bank characteristic and macroeconomic control variables. Interestingly, the size of the coefficient remains robust to the inclusion of control variables, as the sign and significance remain the same, whereas the point estimate decreases slightly in absolute value for all three analyzed specifications.[44]

[42] We refrain from transforming any of our bank-level systemic risk response variables due to the severe loss of information. In particular, a very large number of observations for some variables, such as failed bank assets to sum of assets, take the value of zero. Hence, the use of a logarithm or a log-odds ratio leads to a loss of valuable information. To the best of our knowledge, there is no silver bullet to satisfactorily solve this issue.

[43] The marginal effect is computed as a standardized coefficient, which is obtained by multiplying the unstandardized coefficient (-0.1061, see Column (1) of Table 3) by the ratio of the standard deviations of the independent variable (0.17, see Table 2) and dependent variable (0.0197, see Table 2).

[44] As an example, when we include control variables, a one standard deviation increase in market power is associated with a 0.78 standard deviation reduction in systemic risk. In relative terms, a marginal effect of a 0.78 standard deviation is approximately 18 percent smaller than a 0.92 estimate.

The lagged endogenous variable is significant at the 1 percent level, with a parameter value of approximately 0.29 for the maximum of failed bank assets to the sum of total assets (see Column (2) of Table 3), which supports that this variable has a degree of persistence. However, the lagged dependent variable is not significant for the maximum of the interbank contagion loss as a share of either regulatory capital or RWAs (see Columns (3) to (6) of Table 3)). The validity of the chosen instruments in our specification is satisfactory in all cases, as shown by the failure to reject the Hansen J test (i.e., overidentifying restrictions). There is a significant first-order serial autocorrelation in the residuals and no significant second-order autocorrelation. The F-test suggests that all models are statistically significant at the 5 percent level.

Regarding bank control variables, larger banks are positively correlated with systemic risk because the coefficient of the bank size proxy is positive and significant at the 1 percent for all three systemic risk variables (see Columns (2), (4), and (6) in Table 3). We also find that the coefficient of bank's retail funding ratio, which is a proxy for the bank's liquidity risk, is positive and significant at the 5 percent level for the maximum of the interbank loss to RWAs (see Column (6) in Table 3). The coefficients of bank's retail funding ratio are also positive and significant at the 10 percent level for the other two systemic risk proxy variables (see Column (2) and (4) in Table 3) . We also report that the coefficients for loan-to-assets ratio, provision to assets ratio, capital adequacy ratio, and average risk weight are not significant at the 5 percent level. In this regard, it is interesting to point out that these results suggest that the bank's loan quality seems not to be a relevant factor when including a systemic risk lagged dependent variable in the model. Regarding macro controls, the coefficients for real growth rate of economic activity and its first lag are not significant at the 5 percent level only for the maximum of failed bank assets to the sum of total assets (see Column (2) in Table 3), whereas the coefficients of these two variables are significant at the 5 percent level for the other two systemic risk proxy variables (see Columns (4) and (6) in Table 3). This result is similar to the findings of Jiménez et al. (2013) for which the coefficient of real growth is significant. We also find that the coefficients for the inflation rate are negative and significant at least at the 5 percent level for the three systemic risk proxy variables (i.e., Columns (2), (4), and (6) of Table 3). This result suggests that a one standard deviation increase in the inflation rate (i.e., a 1.08 unit increase in the inflation rate) is associated with a 0.058 standard deviation reduction in systemic risk as measured by failed bank assets to the sum of total assets. This result suggests that a moderate inflation rate not only promotes economic stability but also reduces systemic risk.

Overall, our analysis based on the bank-level Lerner index suggests that regardless of whether we exclude or include control variables, an increase in market power (i.e., a decrease in competition) is associated with more stability (i.e., less systemic risk). To summarize, there is a negative linear relationship between bank-level market power and systemic risk indicators that is highly significant at the 5 percent level. This result supports the previous findings of Hirata and Ojima (2020) for a sample of Japanese regional banks. Even though Hirata and Ojima (2020) and our study apply to a single country, the systemic risk proxy variables and the estimation methodology differ significantly. Our result differs from the common findings reported by Anginer et al. (2014), Leroy and Lucotte (2017), and Silva-Buston (2019), in which more competition enhances stability. This difference is unsurprising, as the dependent variable and estimation techniques differ significantly. In this paper, we study the role played by contagion risk, which is used as a proxy for systemic risk, whereas the outstanding literature has focused on correlation risk as a proxy for systemic risk. It is unclear how our systemic risk proxy variables correlate with those available in the literature because the data required to estimate market-driven measures are not available in Mexico given that only one out of seven D-SIBs is listed on the local stock exchange.

4.2.2 Solvency- or individual-bank-risk-competition nexus

Following the literature (e.g., Anginer et al. (2014), Leroy and Lucotte (2017)), Table 4 presents the coefficient estimates for the linear regression model as described in eq.(2) between two standalone risk measures, namely, the log-odds of the NPL ratio and the logarithm of the Z-score, and the Lerner index. Columns (1) and (2) of Table 4 show the association with the bank-level Lerner index excluding the control variables, whereas Columns (3) and (4) show the association including the control variables. Interestingly, we find that the linear coefficient between the bank-level Lerner index and the two standalone risk measures is not statistically significant. This result differs from that reported by Jiménez et al. (2013) and supports the findings of Zigraiova and Havranek (2016), who report little interplay between bank-level competition and a bank's standalone risk. Explaining that there are two important differences between our study and Jiménez et al. (2013) that possibly drive the reported discrepancy in the results is convenient. First, our study relates to the full banking sector and incorporates both traditional (i.e., pure deposit and loan market activities) and non-traditional (i.e., investment or trading activities) banking activities, whereas the analysis in Jiménez et al. (2013) is restricted to the former. Second, our bank-level Lerner index is not computed at

Table 3: Systemic risk and competition: baseline results using bank level Lerner index

Variables	Max. Failed bank assets to sum of total assets		Max. Interbank loss to regulatory capital		Max. Interbank loss to RWAs	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dep. var.	0.2707***	0.2899***	-0.0607	-0.0784	-0.0460	-0.0575
	(0.0462)	(0.0437)	(0.0870)	(0.0748)	(0.0868)	(0.0741)
Lerner	-0.1061**	-0.0901***	-0.1237***	-0.1076***	-0.0190***	-0.0168***
	(0.0404)	(0.0342)	(0.0430)	(0.0350)	(0.0067)	(0.0054)
Bank size (log Assets)		0.0131***		0.0147***		0.0023***
		(0.0048)		(0.0052)		(0.0008)
Loan to assets ratio		-0.0070		-0.0014		-0.0003
		(0.0087)		(0.0078)		(0.0012)
Retail funding ratio		0.0103*		0.0064*		0.0012**
		(0.0060)		(0.0036)		(0.0006)
Provision to assets ratio		-0.0338		0.0039		0.0009
		(0.0404)		(0.0367)		(0.0058)
Capital adequacy ratio		0.0007		0.0013		0.0002
		(0.0022)		(0.0028)		(0.0004)
Average risk weight		0.0032		-0.0003		0.0001
		(0.0037)		(0.0031)		(0.0005)
Economic activity		-0.0153		-0.0624**		-0.0086*
		(0.0256)		(0.0280)		(0.0046)
Lagged economic activity		0.0429		0.0483**		0.0080**
		(0.0299)		(0.0241)		(0.0039)
Inflation		-0.1057**		-0.1638***		-0.0273***
		(0.0419)		(0.0535)		(0.0087)
Obs.	1,513	1,501	1,513	1,501	1,513	1,501
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0
AR(1) p-value	0.0440	0.038	0.18	0.189	0.162	0.166
AR(2) p-value	0.544	0.564	0.784	0.281	0.74	0.264
Hansen J p-value	0.569	0.621	0.719	0.933	0.617	0.864

Source: Banco de México, authors' calculations.
Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2) $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column pair refers to one out of three systemic risk measures ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

the banking product level. In particular, the bank-level Lerner indices used by Jiménez et al. (2013) are computed for four products: commercial banking receivables, credit lines, all loans (i.e., including mortgages and consumer loans), and deposits.

As in the systemic risk regression, the coefficient for the first lag of the endogenous variable is positive and significant at the 1 percent level. Apparently, persistence is stronger for the Z-score because the point estimate is almost double that of the log-odds NPL ratio.[45] Including the control variables reduces the size of the persistence parameter in both cases. There are two important differences in the estimation process compared with the framework used for the bank-level systemic risk variables. First, we include the first and second lag of the dependent variable because this specification complies with our model validation test. These values show that there is a large degree of persistence in these lagged variables and that persistence is stronger in the case of the Z-score. Second, we use as instruments the second to fifth lag of the competition and standalone risk measures for the bank-level Lerner index and use the second to fifth lag of the standalone risk measures.[46] The Hansen J test is not rejected in any of our four specifications, suggesting that our instruments are satisfactory. In particular, in Columns (2) and (4) of Table 4, the first serial autocorrelation coefficient is significant at the 5 percent level, whereas the second order serial autocorrelation coefficient is not significant. This result confirms that our estimation is valid.

Regarding the bank-level control variables' coefficients, we find mixed evidence for the bank size proxy. Column (3) of Table 4 shows that for the log-odds NPL, the bank size proxy coefficient is not significant. However, we find in Column (4) of Table 4 that for the Z-score, larger banks are associated with a positive and significant coefficient at the 1 percent level. As expected, the loan to assets ratio, which is a proxy for the bank's business model diversification, is a relevant determinant of standalone risk when measured by the log-odds NPL ratio because its coefficient is positive and statistically significant at the 5 percent level. Additionally, as expected, banks with greater capital adequacy ratios have lower standalone risk, suggesting that the availability of capital reduces solvency risk. Moreover, we find that an increase in the average risk weight has a negative and significant coefficient with the Z-score, but it remains insignificant for the NPL. Surprisingly, we also find that the coefficients for macroeconomic control variables are not statistically significant.

[45]Columns (2) and (4) in Table 4 show that the point estimates for the Z-score (NPL) are 0.92 (0.59), and 0.90 (0.53) depending on whether the control variables are excluded or included.

[46]Alternative lags were used, and we obtained qualitatively similar results.

Table 4: Stand-alone risk and competition: baseline results using bank level Lerner index

Variables	log-odds NPL (1)	log Z-score (2)	log-odds NPL (3)	log Z-score (4)
Lag 1 dep. Var.	0.5856***	0.9227***	0.5344***	0.9055***
	(0.1357)	(0.1480)	(0.1896)	(0.1284)
Lag 2 dep. Var.	0.0770	-0.2986***	0.0682	-0.3057***
	(0.0857)	(0.0733)	(0.0904)	(0.0680)
Lerner	0.8684	-0.0614	0.8628	-0.1496
	(0.6199)	(0.2748)	(0.8658)	(0.2773)
Bank size (log Assets)			-0.0856	0.3570***
			(0.1561)	(0.0759)
Loan to assets ratio			1.3357**	0.1769
			(0.5450)	(0.2616)
Retail funding ratio			-0.0490	0.0723
			(0.2716)	(0.1118)
Provision to assets ratio			-5.7315**	-0.5093
			(2.6146)	(1.7323)
Capital adequacy ratio			-3.4011***	0.2755**
			(1.2987)	(0.1192)
Average risk weight			-0.5592	0.4447**
			(0.4247)	(0.1803)
Economic activity			-0.2938	0.1484
			(0.6944)	(0.7101)
Lagged economic activity			-0.0121	0.0963
			(0.9427)	(0.4923)
Inflation			2.5322	-0.0191
			(1.6613)	(1.8035)
Obs.	1,213	1,433	1,213	1,433
Year dummies	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0
AR(1) p-value	0.129	0.0298	0.155	0.0100
AR(2) p-value	0.588	0.115	0.568	0.754
Hansen J p-value	0.361	0.212	0.314	0.497

Source: Banco de México, authors' calculations.
Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where $SR_{i,t}$ refers to one of the stand-alone risk measures. Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments from the second to the fifth lag of the competition and stand-alone risk measures for the bank level Lerner index. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

4.2.3 Effect of the 2014 financial reform on the nexus between systemic risk and competition at the bank level

In the previous section, we have shown that more market power intensity is negatively correlated with systemic risk, consistent with the perception that market power provides banks with incentives to take on less diverse risks. However, the impact of market power intensity may depend on regulatory changes that can mitigate or exacerbate the systemic-risk-competition nexus. In Mexico, financial authorities introduced a financial reform in 2014 to promote competition between financial intermediaries (i.e., bank and non-bank financial intermediaries). The main objective of the reform was to reduce several different market failures. Interestingly, Bátiz-Zuk and Lara-Sánchez (2022) find that according to the bank-level Lerner index, empirical evidence exists to support the idea that the reform had a positive average effect and increased the annual variation in banks' competition measure for a few years. However, they document that significant heterogeneity also exists at the bank level, as some large banks benefited from an increase in their market power. In the literature, Anginer et al. (2014) analyze how each country's regulatory and institutional environment influences the bank's systemic stability and how it affects the nexus between bank competition and systemic stability. In this section, we examine whether the 2014 financial reform affects a bank's systemic stability by using the following regression model:

$$SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \kappa(D_t * C_{i,t}) + \theta(1 - D_t) * C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}. \quad (11)$$

As before, our dependent variable is the individual bank's systemic risk at time t. We use exactly the same controls as those defined in the Methodology section. The regression specification is similar to eq.(2) except that we now include a binary discrete variable that interacts with the bank's Lerner index variable. In eq.(11), we use a dummy variable D_t that takes the value of one during the period previous to the implementation of the 2014 financial reform, whereas $(1 - D_t)$ takes the value of one once the reform was implemented. The objective is to identify the sign and statistical significance of θ and to assess whether the reform strengthens or mitigates the risk-competition nexus if it differs from κ.

We expect that the implementation of a package of competition measures is associated, on average, with less market power, which could increase systemic risk through the search for yield channel. According to this channel, if banks cannot open new profitable lines of businesses, then more competition may lead them to take on more risk in their portfolios and to exhibit herd behavior, which would increase the correlation risk in banks' risk taking at the sector level. In summary, this search for yield channel leads banks to increase risk taking in the interbank market, which would contribute to increase systemic risk at the bank level.

Columns (1) to (3) of Table 5 present the systemic coefficient estimates for bank-level regressions with bank competition interacted with our regulatory dummy variables included as explanatory variables. We use the Wald test to assess whether the two coefficients for the interaction term differ (i.e., whether $H_0 = \kappa = \theta$). The fact that we cannot reject the Wald test at the 10 percent level provides evidence that the 2014 financial reform did not affect the sign or magnitude between market power and systemic risk. We conclude that the reform did not affect the relationship between systemic risk and competition at the bank level.

Regarding the effect of the regulation with the solvency risk indicators, we expect that there should be no effect. This is because we previously found that there was no interplay between solvency risk and market power. The Wald statistic p-value in Columns (4) and (5) of Table 5 suggests that the 2014 financial reform exerted no effect on the relationship between market power and solvency risk. The fact that the Wald statistic p-value in Column (4) of Table 5 is significant at the 10 percent level may be because the NPL indicator is very sensitive to a spike that occurred between 2013 and 2014 and that is attributed to an increase in impaired loans in the construction sector (see Iakova et al. (2014)). Thus, we have reason to believe that the dummy variable is somehow picking up this effect.

4.3 Robustness tests

To assess the strength of our findings, we consider a battery of robustness checks using supplementary systemic risk statistics, alternative competition measures, data with a finer time frequency, varying bankruptcy thresholds of the regulatory capital ratio, sample selection criteria, and a supplementary estimation method. The results can be found in Appendix B.

Table 5: Systemic risk and competition: interaction with 2014 financial reform using bank level Lerner index

Variables	Max. Failed bank assets to sum of total assets (1)	Max. Interbank loss to regulatory capital (2)	Max. Interbank loss to RWAs (3)	log-odds NPL (4)	log Z-score (5)
Lag 1 dep. var.	0.3157***	-0.0523	-0.0382	0.5073**	0.9425***
	(0.0539)	(0.0895)	(0.0827)	(0.2150)	(0.1233)
Lag 2 dep. var.				0.0727	-0.3254***
				(0.0996)	(0.0684)
$Lerner \times D_t$	-0.1044**	-0.1046**	-0.0163**	0.4681	-0.1744
	(0.0516)	(0.0433)	(0.0065)	(1.0718)	(0.2757)
$Lerner \times (1 - D_t)$	-0.0305	-0.1409***	-0.0216***	4.1258**	0.0724
	(0.0326)	(0.0462)	(0.0072)	(1.9067)	(0.8634)
Bank size (log Assets)	0.0107**	0.0166***	0.0026***	-0.1411	0.3492***
	(0.0047)	(0.0052)	(0.0008)	(0.1450)	(0.0831)
Loan to assets ratio	-0.0047	0.0005	-0.0000	1.0683**	0.1754
	(0.0101)	(0.0097)	(0.0015)	(0.5266)	(0.2437)
Retail funding ratio	0.0087	0.0057	0.0011*	-0.0296	0.0639
	(0.0062)	(0.0040)	(0.0007)	(0.2558)	(0.1098)
Provision to assets ratio	-0.0061	-0.0078	-0.0000	-4.6135*	-0.4722
	(0.0399)	(0.0437)	(0.0069)	(2.7323)	(1.5411)
Capital adequacy ratio	0.0014	0.0007	0.0001	-3.4822**	0.2836**
	(0.0024)	(0.0029)	(0.0005)	(1.3701)	(0.1153)
Average risk weight	0.0019	0.0001	0.0001	-0.4937	0.4780***
	(0.0039)	(0.0038)	(0.0006)	(0.3834)	(0.1853)
Economic activity	-0.0087	-0.0548	-0.0074	-0.2774	0.0480
	(0.0294)	(0.0376)	(0.0058)	(0.8299)	(0.6849)
Lagged economic activity	0.0486	0.0353	0.0063	-0.0079	0.1218
	(0.0334)	(0.0253)	(0.0040)	(0.8646)	(0.4745)
Inflation	-0.1055**	-0.1647***	-0.0267***	3.0680*	0.0974
	(0.0461)	(0.0635)	(0.0102)	(1.7014)	(1.7907)
Obs.	1,501	1,501	1,501	1,213	1,433
Year dummies	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0
AR(1) p-value	0.0401	0.19	0.168	0.161	0.00307
AR(2) p-value	0.605	0.696	0.624	0.664	0.811
Hansen J p-value	0.781	0.505	0.621	0.758	0.597
Wald test (H_0: $\kappa = \theta$) p-value	0.243	0.525	0.502	0.080	0.794

Source: Banco de México, authors' calculations.
Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(11), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta_1 C_{i,t} \times D_t + \beta_2 C_{i,t} \times (1 - D_t) + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to a different systemic risk measure ($SR_{i,t}$) in particular $SR_{i,t}$ is failed bank assets to sum of total assets in column (1), interbank loss to regulatory capital in column (2), interbank loss to RWAs in column (3). D_t is a dummy variable that takes a value of one before 2014 and zero afterwards, whereas $(1 - D_t)$ is a dummy variable that takes a value of one after 2014. Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

5 Conclusions

Although it is undeniable that more intense competition brings many benefits for users of financial services, especially in terms of cost reduction and product differentiation, it is not yet theoretically clear whether this competition has a positive or a negative effect on bank risk taking and, ultimately, on the stability of the financial system. A debate is ongoing among academics, industry representatives, and policymakers regarding the benefits and costs of the relationship between competition and bank-level risk. To date, no evidence of a robust relationship between bank competition, bank soundness, and financial stability exists. Moreover, most papers in the literature have analyzed only an individual bank's risk; only a few have investigated the systemic-risk-competition nexus.

In this paper, we propose and study new mechanisms that operate behind the systemic-risk-competition nexus at the bank level in the interbank market. We follow a comprehensive approach using quarterly data of the Mexican banking sector from 2008 to 2019 and contribute to the analysis of the relationship between bank competition and systemic stability. In this line of research, as a proxy to systemic risk, the use of counterfactual network theory indicators designed to capture the direct contagion risk in the interbank market is new, as in this market, traditionally, only market-driven systemic risk proxies, such as CoVaR, SRISK, MES, or standalone bank risk measures, have been studied. The ultimate objective is to assess how counterfactual contagion risk in the interbank market relates to more intense competition in the banking sector. We also follow the traditional literature and evaluate the interaction between bank-level standalone risk measures and the two competition measures. In addition, we study whether the 2014 financial reform, which is a package of measures designed to promote competition (i.e., internal regulatory shock), intensifies or reduces the interaction between systemic risk and competition at the bank level. A number of robustness tests were also performed.

We have three noteworthy findings related to bank-level systemic risk. First, our results for the bank-level Lerner index suggest that a robust negative relationship exists between market power and systemic risk, implying that more intense bank-level market power (less competition) is associated with a reduction in systemic risk. Second, we find that solvency or individual bank risk indicators (i.e., non-performing loan ratio and the Z-score) are not affected by more intense market power. This result supports the previous findings of Zigraiova and Havranek (2016) and enforces the perception that the "competition-fragility" and the "competition-stability" paradigms fail to characterize the link between risk and competition. This result is unsurprising because standalone risk measures are based on balance sheet information that is not forward-looking and fails to incorporate the issue of interconnections among bank entities.[47] Third, we find that the 2014 financial reform had no impact on the association between market power and systemic risk at the bank level. The results of robustness tests remained robust in all cases. The literature and this paper are both limited in that competition and the risk of non-bank financial intermediaries and their interactions are not considered.

Our paper has one important lesson for policy-making decision purposes. We argue that policymakers should monitor the evolution of competition measures and disentangle the link between systemic and solvency risk indicators. Regulators and supervisors should monitor the composition of the banking sector and promote policies that provide incentives for banks to diversify their operations with as many counterparts as possible in the interbank market to mitigate potential sources of interconnectedness stemming from relationship lending that may increase with an increase in a bank's market power.

References

Acemoglu, D., Ozdaglar, A., and Tahbez-Salehi, A. (2015). Systemic risk and financial stability in networks. *American Economic Review*, 105(2):564–608.

Acharya, V. V. and Yorulmazer, T. (2008). Information contagion and bank herding. *Journal of Money, Credit and Banking*, 40(1):215–231.

Adrian, T. and Brunnermeier, M. K. (2011). CoVaR. *National Bureau of Economic Research Working Paper*, No. 17454.

Affinito, M. (2012). Do interbank customer relationships exist? And how did they function in the crisis? Learning from Italy. *Journal of Banking & Finance*, 36(12):3163–3184.

Afonso, G., Kovner, A., and Schoar, A. (2013). Trading partners in the interbank lending market. *Federal Reserve Bank of New York Working Paper*, No. 620.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, 120(2):701–728.

[47] In fact, these risk indicators have several shortcomings, such as their sensitivity to the transferring of non-performing loans to asset management companies from banks' balance sheets and the subsequent underestimation of risk in the loan portfolio.

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33.

Anginer, D., Demirguc-Kunt, A., and Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation*, 23(1):1–26.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297.

Bátiz-Zuk, E. and Lara-Sánchez, J. L. (2022). Measuring the evolution of competition and the impact of the financial reform in the Mexican banking sector, 2008-2019. *Research in International Business and Finance*, 59.

Bátiz-Zuk, E., López-Gallo, F., Martínez-Jaramillo, S., and Solórzano-Margain, J. P. (2016). Calibrating limits for large interbank exposures from a system-wide perspective. *Journal of Financial Stability*, 27:198–216.

Beck, T. (2008). Bank competition and financial stability: Friends or foes? *World Bank Policy Research Working Paper*, No. 4656.

Beck, T., De Jonghe, O., and Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, 22(2):218–244.

Beck, T., Demirgüç-Kunt, A., and Levine, R. (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance*, 30(5):1581–1603.

Berger, A. N., Klapper, L. F., and Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, 35(2):99–118.

Boot, A. W. and Thakor, A. V. (1993). Self-interested bank regulation. *The American Economic Review*, 83(2):206–212.

Boyd, J. H. and De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance*, 60(3):1329–1343.

Bräuning, F. and Fecht, F. (2017). Relationship lending in the interbank market and the price of liquidity. *Review of Finance*, 21(1):33–75.

Brei, M., Jacolin, L., and Noah, A. (2020). Credit risk and bank competition in Sub-Saharan Africa. *Emerging Markets Review*, 44:1–19.

Buch, C. M., Koch, C. T., and Koetter, M. (2013). Do banks benefit from internationalization? Revisiting the market power–risk nexus. *Review of Finance*, 17(4):1401–1435.

Canedo, J. M. D. and Jaramillo, S. M. (2009). A network model of systemic risk: Stress testing the banking system. *Intelligent Systems in Accounting, Finance & Management: International Journal*, 16:87–110.

Carletti, E. (2008). Competition and regulation in banking. *Handbook of Financial Intermediation and Banking*, 126(5):449–482.

Cerutti, E., Claessens, S., and McGuire, P. (2014). Systemic risks in global banking: What available data can tell us and what more data are needed? *University of Chicago Press*.

Claessens, S. (1998). Comment on banking in transition economies: Does efficiency require instability. *Journal of Money, Credit and Banking*, 30(3):651–655.

Claessens, S. and Laeven, L. (2004). What drives bank competition? Some international evidence. *Journal of Money, Credit and Banking*, 36(3):563–583.

Cocco, J. F., Gomes, F. J., and Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, 18(1):24–48.

Cole, R. A. and White, L. J. (2012). Déjà vu all over again: the causes of US commercial bank failures this time around. *Journal of Financial Services Research*, 42:5–29.

Craig, B. and Von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation*, 23(3):322–347.

Craig, B. R., Fecht, F., and Tümer-Alkan, G. (2015). The role of interbank relationships and liquidity needs. *Journal of Banking & Finance*, 53:99–111.

De Bandt, O., Hartmann, P., and Peydro, J.-L. (2009). Systemic risk in banking: An update. *Berger, A., MP, Wilson, J.(Eds.), Oxfoord Handbook of Banking. Oxford University Press, Oxford*.

de Ramon, S., Francis, W., and Straughan, M. (2018). Bank competition and stability in the United Kingdom. *Bank of England Working Paper*, No. 748.

de Ramon, S., Francis, W., and Straughan, M. (2020). The link between bank competition and risk in the United Kingdom: Two views for policymaking. *Bank of England Working Paper*, No. 885.

de Ramon, S. and Straughan, M. (2020). The evolution of competition in the UK deposit-taking sector, 1989–2013. *The European Journal of Finance*, 26(10):958–977.

Degryse, H., Kim, M., and Ongena, S. (2009). Microeconometrics of banking: Methods, applications, and results. *Oxford University Press, USA*.

Degryse, H., Nguyen, G., et al. (2007). Interbank exposures: An empirical examination of contagion risk in the Belgian banking system. *International Journal of Central Banking*, 3(2):123–171.

Degryse, H. and Ongena, S. (2008). Competition and regulation in the banking sector: A review of the empirical evidence on the sources of bank rents. *Handbook of Financial Intermediation and Banking*, :483–554.

Dell'Ariccia, G. and Marquez, R. (2004). Information and bank credit allocation. *Journal of Financial Economics*, 72(1):185–214.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

Freixas, X., Parigi, B. M., and Rochet, J.-C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, 32(3):611–638.

Furfine, C. H. (2003). Interbank exposures: Quantifying the risk of contagion. *Journal of Money, Credit and Banking*, 35(1):111–128.

Gai, P. and Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 466:2401–2423.

Galati, G. and Moessner, R. (2013). Macroprudential policy–a literature review. *Journal of Economic Surveys*, 27(5):846–878.

Guerrero-Gómez, S. and Lopez-Gallo, F. (2004). Interbank exposures and systemic risk assessment: An empirical analysis for the Mexican banking sector. *Mimeo*.

Hakenes, H. and Schnabel, I. (2010). Banks without parachutes: Competitive effects of government bail-out policies. *Journal of Financial Stability*, 6(3):156–168.

Haldane, A. G. (2013). Rethinking the financial network. In *Fragile stabilität–stabile fragilität*, pages 243–278. Springer.

Hauswald, R. and Marquez, R. (2006). Competition and strategic information acquisition in credit markets. *The Review of Financial Studies*, 19(3):967–1000.

Hirata, W. and Ojima, M. (2020). Competition and bank systemic risk: New evidence from Japan's regional banking. *Pacific-Basin Finance Journal*, 60:1–36.

Iakova, D., Kamil, H., Valencia, F., de Imus, P., Rial, I., Zhou, J., and Rennhack, M. (2014). Staff report for the 2014 Article IV Consultation - Mexico. *International Monetary Fund*.

Iori, G., Reno, R., De Masi, G., and Caldarelli, G. (2007). Trading strategies in the Italian interbank market. *Physica A: Statistical Mechanics and its Applications*, 376:467–479.

Iyer, R. and Peydró-Alcalde, J.-L. (2005). How does a shock propagate? A model of contagion in the interbank market due to financial linkages. In *Proceedings of the European Finance Association Annual Meetings*.

Jiménez, G., Lopez, J. A., and Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, 9(2):185–195.

Karas, A., Schoors, K., et al. (2012). Bank networks, interbank liquidity runs and the identification of banks that are too interconnected to fail. In *Second CInST Banking Workshop, Moscow*.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review*, 80(5):1183–1200.

Leon, F. (2015). Measuring competition in banking: A critical review of methods. *Centre D'études et de Recherches Sur Le Développement International (CERDI)*, No. 12.

Lerner, A. (1934). The concept of monopoly and the measurement of monopoly power. *The Review of Economic Studies*, 1(3):157–175.

Leroy, A. and Lucotte, Y. (2017). Is there a competition-stability trade-off in European banking? *Journal of International Financial Markets, Institutions and Money*, 46:199–215.

Levine, R., Demirgüç-Kunt, A., and Beck, T. (2007). Bank concentration and fragility: Impact and mechanics. *University of Chicago Press*, :193–234.

Martínez-Jaramillo, S., Pérez, O. P., Embriz, F. A., and Dey, F. L. G. (2010). Systemic risk, financial contagion and financial fragility. *Journal of Economic Dynamics and Control*, 34(11):2358–2374.

Martinez-Miera, D. and Repullo, R. (2010). Does competition reduce the risk of bank failure? *The Review of Financial Studies*, 23(10):3638–3664.

Maudos, J. and De Guevara, J. F. (2007). The cost of market power in banking: Social welfare loss vs. cost inefficiency. *Journal of Banking & Finance*, 31(7):2103–2125.

Memmel, C., Sachs, A., and Stein, I. (2012). Contagion in the interbank market with stochastic loss given default. *International Journal of Central Banking*, 8(3):177–206.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2):449–470.

Mistrulli, P. E. (2005). Interbank lending patterns and financial contagion. *The Bank of Italy Working Paper*.

Mistrulli, P. E. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of Banking & Finance*, 35(5):1114–1127.

Poledna, S., Molina-Borboa, J. L., Martínez-Jaramillo, S., Van Der Leij, M., and Thurner, S. (2015). The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *Journal of Financial Stability*, 20:70–81.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system gmm in stata. *The Stata Journal*, 9(1):86–136.

Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1):135–158.

Schaeck, K. and Cihák, M. (2014). Competition, efficiency, and stability in banking. *Financial Management*, 43(1):215–241.

Schaeck, K., Cihak, M., and Wolfe, S. (2009). Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, 41(4):711–734.

Silva-Buston, C. (2019). Systemic risk and competition revisited. *Journal of Banking & Finance*, 101:188–205.

Soedarmono, W., Machrouh, F., and Tarazi, A. (2011). Bank market power, economic growth and financial stability: Evidence from Asian banks. *Journal of Asian Economics*, 22(6):460–470.

Solorzano-Margain, J. P., Martinez-Jaramillo, S., and Lopez-Gallo, F. (2013). Financial contagion: Extending the exposures network of the Mexican financial system. *Computational Management Science*, 10(2):125–155.

Spierdijka, L. and Zaourasa, M. (2018). Measuring banks' market power in the presence of economies of scale: A scale-corrected Lerner index. *Journal of Banking & Finance*, 87:40–48.

Tabak, B. M., Fazio, D. M., and Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking & Finance*, 36(12):3366–3381.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*, 7(3):111–125.

Upper, C. and Worms, A. (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review*, 48(4):827–849.

van Lelyveld, I. and Liedorp, F. (2006). Interbank contagion in the Dutch banking sector. *International Journal of Central Banking*, 2:99–132.

Wells, S. J. (2004). Financial interlinkages in the United Kingdom's interbank market and the risk of contagion. *Bank of England Working Paper*, No. 230.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1):25–51.

Zigraiova, D. and Havranek, T. (2016). Bank competition and financial stability: Much ado about nothing? *Journal of Economic Surveys*, 30(5):944–981.

Appendix A

In this section, we provide additional empirical statistical analysis related to our paper that serves as supplement and/or reference. We have structured this section, such that each item appears in sequential order as discussed in the paper. We believe that the information content is either too general or too detailed to include in the main text of the paper. Table A1 presents the variable definitions used in our paper. Table A2 shows the correlation matrices between our risk and competition measures. Additionally, Table A3 shows the correlation matrix between our independent variables (i.e., competition measures as well as bank-level and macro control variables). As a reference for robustness, Table A4 shows the summary statistics when the threshold for bank failure minimum regulatory capital in the sequential default algorithm increases from 8 to 10.5 percent.

Figure A1 shows the evolution of the distribution of failed bank assets to sum of total assets. Figure A2 shows the evolution of interbank losses as a percentage of regulatory capital, whereas Figure A3 shows the evolution of interbank losses as a percentage of risk-weighted assets. Each Figure has a number of panels used to identify and distinguish the metric under analysis (e.g., Panel A shows the Average; Panel B shows the Median; Panel C shows the VaR (75%); Panel D shows the VaR (90%); Panel E shows VaR (95%); Panel F shows VaR (97.5%); Panel G shows the E.S.(95%) or CVaR (95%); Panel H shows the E.S. (97.5%) or CVaR(97.5%); and Panel I shows the Maximum value that corresponds to the worst contagion chain. In turn, Panel A and B in Figure A4 show the evolution of the distribution of our two secondary systemic risk measures: average NBF and average SBF, respectively. Note that as the confidence level of our VaR or E.S. measures increases, the size and variability between the '10th/90th percentiles' and the '25th/75th percentiles' increases. Additionally, as we move away from the mean to consider tail statistics, we identify that there is an increase in the loss level.

Panel A and B in Figure A5 show the evolution of the distribution of our two standalone risk measures (i.e., non-performing loans ratio and Z-score). As discussed in the main text, the NPL ratio has a remarkable spike in half-2013 and there are other less noticeable spikes over 2008-2010. Moreover, the size of the range of values between the 10th and the 90th percentiles widen starting 2014. Regarding the Z-score, its distribution evolution has a minimum value over the global financial crisis period 2008-2009. Since both the mean and median value of this indicator follow an upward trend over our sample period, this suggests that the risk of insolvency for the average or median bank has decreased. Figure A6 shows the bank-level Lerner index distribution. Specifically, we display the mean and median values across all banks that form part of this study along with the interval between the 25th and 75th percentiles. The mean and the median of the Lerner index distribution have a similar behavior over the whole sample period.[48] Figure A7 shows the joint evolution between the average and the maximum of the worst case systemic risk measures. Figure A8 shows a scatter diagram to explore the nature of the empirical relation between two of our primary systemic risk measures and the standalone risk measures (y-axis) and the bank-level Lerner index (x-axis), whereas Figure A9 shows the empirical relation between the bank-level Lerner index and the rest of our systemic risk measures.

[48]Even when the theoretical value of the bank-level Lerner index cannot be negative, in our estimates we do observe negative values for some banks in a few quarters (i.e., 20 banks, all of them small) The number of bank-quarter observations represent less than 10 percent of our sample.

Table A1: Variable definitions

Variables ($symbol$) **[unit of analysis]**	**Description**	**Source** (P=Proprietary)
Dependent variables: primary systemic risk measures		
Failed bank assets to sum of assets (FA_{it}/A_t) [Unit free]	For each quarter, we compute the daily ratio of failed bank assets to sum of assets in the banking sector at the bank level (i.e., the loss in asset value excluding the idiosyncratic bank failure) using the results of the sequential default algorithm. This leads approximately to 60 point in time values for each bank. Then, we group the 60 daily values available in each quarter for each bank and compute a quarterly empirical distribution at the bank level. Moreover, we use this information to compute four bank-level risk statistics (i.e., Mean, VaR (95%), E.S.(95%) or CVaR(95%) and Maximum). The Maximum is the value that corresponds to the worst contagion chain. The worst contagion chain for the period is identified as the point at which the share in total assets that is lost from bank failures as a result of contagion risk (i.e., excluding the trigger bank) is highest.	Banxico (P)
Interbank loss (IL_{it}) [Unit free]	For each quarter, we compute the daily interbank loss in the banking sector at the bank level (i.e., the loss excluding the idiosyncratic bank failure) as the sum of counterfactual bank losses as a result of contagion using the results of the sequential default algorithm. We sum all bank losses irrespective of whether banks fail. This leads approximately to 60 point in time values for each bank. Then, we group the 60 daily values available in each quarter for each bank and compute a quarterly empirical distribution at the bank level.	Banxico (P)
Ratio of interbank loss to regulatory capital (IL_{it}/RC_t) [Unit free]	For each bank, this variable is defined as the ratio between the daily sum of interbank loss as a result of contagion to the sum of regulatory capital (i.e., Tier1 plus Tier 2 capital) in the banking sector. Since we have a quarterly empirical distribution at the bank level, we compute four bank-level risk statistics (i.e., Mean, VaR (95%), E.S.(95%) or CVaR(95%) and Maximum). The Maximum is the value that corresponds to the worst contagion chain. The worst contagion chain for the period is identified as that point at which we find the greatest interbank loss as a result of contagion as share of banking sector regulatory capital (i.e., excluding the trigger bank).	Banxico (P)
Ratio of interbank loss to risk-weighted assets (IL_{it}/RWA_t) [Unit free]	For each bank, this variable is defined as the ratio between the daily sum of interbank loss as a result of contagion to the sum of risk-weighted assets (RWAs) in the banking sector. Since we have a quarterly empirical distribution at the bank level, we compute four bank-level risk statistics (i.e., Mean, VaR (95%), E.S.(95%) or CVaR(95%) and Maximum). The Maximum is the value that corresponds to the worst contagion chain. The worst contagion chain for the period is identified as that point at which we find the greatest interbank loss as a result of contagion as share of banking sector risk-weighted assets (i.e., excluding the trigger bank).	Banxico (P)

Table A1. (Continued)

Variables $(symbol)$ [unit of analysis]	Description	Source (P=Proprietary)
Dependent variables: secondary systemic risk measures		
NBF (NBF_{it}) [Unit free]	For each bank at each point in time t (where t is a working day over any quarter), this variable refers to the number of banks that fail as a consequence of each idiosyncratic bank failure (we do not consider the idiosyncratic bank failure) using the results of the sequential default algorithm. This leads approximately to 60 point in time values for each bank. It is possible to group the 60 daily values available in each quarter for each bank and compute a quarterly empirical distribution at the bank level. Moreover, we use this information to compute the bank-level average of the quarterly interbank number of banks that fail as a consequence of each idiosyncratic bank failure.	Banxico (P)
SBF (SBF_{it}) [Unit free]	For each point in time t (where t is a working day over any quarter), this variable is the number of times that a specific bank fails as a consequence of the idiosyncratic failure (SBF) of any other bank using the results of the sequential default algorithm. This leads approximately to 60 point in time values for each bank. It is possible to group the 60 daily values available in each quarter for each bank and compute a quarterly empirical distribution at the bank level. Moreover, we use this information to compute the bank-level average of the quarterly interbank number of times that a specific bank fails as a consequence of the idiosyncratic failure of any other bank.	Banxico (P)
Dependent variables: standalone risk measures		
Non-performing loans ratio [Unit free]	For each bank, this is defined as the ratio of non-performing loan size to total loan size (i.e., denominator includes the sum of both performing and non-performing loans)).	CNBV
Z-score [Unit free]	For each bank, the Z-score is the bank return on assets (i.e., ROA is defined as net income divided by total assets) plus bank equity to assets ratio, scaled by the standard deviation of return on assets over the previous 2 years (i.e., we use a 2-year rolling window standard deviation of ROA in the denominator). This is a traditional accounting based measure computed for each quarter.	CNBV

Table A1. (Continued)

Variables ($symbol$) **[unit of analysis]**	**Description**	**Source** (P=Proprietary)
Competition measures		
Bank-level Lerner index [Unit free]	This is a bank-level measure defined as the ratio of the output price minus marginal cost to output price. The marginal cost is estimated from a trans-log cost function. Following the literature, we use as a proxy for output price the bank's total interest and non-interest revenue per output unit, and we use bank's total assets as a proxy for the bank's output.	Banxico (P) and CNBV
Weighted aggregate Lerner index [Unit free]	This is a time-varying banking sector measure defined as the weighted average of the bank-level Lerner index. The weight is the bank's market share where total assets is used as a proxy for bank size.	Banxico (P) and CNBV
Boone indicator [Unit free]	This is a time-varying banking sector measure defined as a β_t coefficient estimate for each period t from a profitability equation. This indicator takes into account the aggressiveness of competitors' conducts in the market.	Banxico (P) and CNBV
Market share [Unit free]	This is a bank-level variable defined as the ratio of bank's asset size to sum of assets in the banking sector.	Banxico (P) and CNBV
Herfindahl-Hirschman index [Unit free]	This is a time-varying banking sector measure that provides a reliable indicator of market concentration. For each period t, we sum the square of the market share using bank's total asset as a proxy for size.	Banxico (P) and CNBV

Table A1. (Continued)

Variables ($symbol$) **[unit of analysis]**	**Description**	**Source** (P=Proprietary)
Bank-control variables		
Bank assets (Q_{it}) [MXN in millions]	This variable is used as a measure of bank's scale and total output. For the quarterly frequency, it is measured as the end-of-month value reported for each quarter.	CNBV
Loans to assets ratio (L_{it}/Q_{it}) [Unit free]	For each bank, the numerator is computed as the sum of all bank loans to private non-financial entities, whereas the denominator is total assets as defined in this Table.	CNBV
Retail funding to total liabilities ratio. (RF_{it}/TL_{it}) [Unit free]	For each bank, the numerator is the size of bank's customers total deposits, whereas the denominator is the bank's total liabilities.	CNBV
Provisions to assets ratio (PR_{it}/Q_{it}) [Unit free]	For each bank, the numerator is computed as the sum of loan loss allowance for non-financial private entities, whereas the denominator are the bank's assets as defined in this Table.	CNBV
Capital adequacy ratio (CAR_{it}) [Unit free]	For each bank, the capital to assets ratio is calculated as regulatory capital divided by total assets.	CNBV
Average risk weight (ARW_{it}) [Unit free]	For each bank, the numerator is computed as the total amount of bank's risk-weighted assets, whereas the denominator is the bank's total assets as defined in this Table.	Banxico
Macroeconomic control variables		
Economic activity index YoY (EAI_{it}) [%]	The index of global economic activity (IGAE, its acronym in Spanish) is a short-term (monthly) indicator that serves as a proxy for GDP. The index is computed as the result of weighted data on production from all the sectors in the economy, and follows the same methodology of the National Accounting System. In particular, IGAE incorporates primary, secondary and tertiary activities, excluding: fishing, forestry, corporate and other service activities. This series is seasonally adjusted.	INEGI
Inflation rate (IR_{it}) [%]	Computed based on the Consumer Price Index.	INEGI

Table A1. (Continued)

Variables ($Acronym$) **(unit of analysis)**	**Description**	**Source** (P=Propietary)
Auxiliary variables used to estimate competition and risk measures		
Bank funding costs ($W_{it}^{(1)}$) [Unit free]	For each bank, the numerator is computed as the sum of the interest expenses over the past year, whereas the denominator is the average of bank's total asset for the past year. This variable is a proxy for bank funding costs.	CNBV
Bank Labor expenses ($W_{it}^{(2)}$) [Unit free]	For each bank, the numerator is computed as the sum of the employees remunerations (i.e., wages, salaries, bonuses and compensations) over the past year, whereas the denominator is the average of bank's total assets over the past year.	Banxico (P)
Operational costs ($W_{it}^{(3)}$) [Unit free]	Operational costs (fixed expenses) For each bank, the numerator is computed as the sum of the operational expenses (i.e., non-interest and non-labour related) over the past year, whereas the denominator is the average of bank's total assets over the past year.	CNBV
Total revenues (TR_{it}) [MXN in millions]	This variable is the sum of bank's revenue stemming from charging: interest, fees and other financial services over the past year.	CNBV
Total costs (C_{it}) [MXN in millions]	For each bank, this variable is the sum of bank's costs stemming from: interest expenses, increases in loan loss provisions, fee payments, employees and personnel expenses, operational costs and other expenses, over the past year.	Banxico (P) and CNBV
Revenues to assets ratio (P_{it}) [Unit free]	For each bank, this variable is the ratio of total revenue to total assets as defined in this Table.	CNBV
Profits to assets ratio (π_{it}) [Unit free]	For each bank, the numerator is computed as the sum of profits over the past year, whereas the denominator is the banks assets as defined in this Table.	Banxico (P) and CNBV
Costs to revenues ratio ($\hat{C}_{it}$) [Unit free]	For each bank, this is the ratio of total cost to total revenue as defined in this Table.	Banxico (P) and CNBV
Revenues to costs ratio (RC_{it}) [Unit free]	For each bank, this is the ratio of total revenue to total costs as defined in this Table.	Banxico (P) and CNBV
Return on assets (ROA_{it}) [Unit free]	For each bank, the numerator is computed as profits after tax, whereas the denominator are the bank's assets as defined in this Table.	CNBV

Source: Banco de México, authors' calculations.

Notes: This Table provides variable definitions for endogenous and exogenous variables. Regarding the endogenous variables, in this paper we consider twelve primary and two secondary systemic risk measures along with two standalone risk measures. Additionally, we provide definition for six competition measures; six bank-control variables and two macroeconomic control variables. Finally, we include a set of auxiliary variables used to estimate our competition measures and this is fully described in Bátiz-Zuk and Lara-Sánchez (2022). A publicly available version of bank-level variables is published in the website of CNBV (https://portafolioinfo.cnbv.gob.mx/Paginas/Inicio.aspx; accessed on December 23, 2020). The last Column in this Table shows the source of our data were: CNBV is the acronym in Spanish for the National Banking and Securities Commission; INEGI is the acronym in Spanish for the National Institute of Statistics and Geography; and Banxico is the acronym in Spanish for the Central Bank of Mexico. All variables are available on a quarterly basis.

Table A2: Correlation matrix between systemic risk measures and competition measures

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Avg. of failed assets to sum of assets (%)	1	0.92^a	0.9^a	0.84^a	0.8^a	0.78^a	0.77^a	0.76^a	0.78^a	0.77^a	0.76^a	0.75^a	0.83^a	-0.1^a	0.25^a	0	0.08^a	-0.01	-0.06^b	0.55^a
2	VaR 95% of failed assets to sum of assets (%)		1	0.98^a	0.91^a	0.81^a	0.82^a	0.82^a	0.81^a	0.8^a	0.81^a	0.81^a	0.8^a	0.83^a	-0.1^a	0.27^a	0.01	0.07^a	0	-0.04^c	0.61^a
3	E.S. at 95% of failed assets to sum of assets (%)			1	0.96^a	0.84^a	0.85^a	0.85^a	0.84^a	0.83^a	0.84^a	0.84^a	0.84^a	0.84^a	-0.11^a	0.28^a	0	0.06^b	0.01	-0.03	0.65^a
4	Max. of failed assets to sum of assets (%)				1	0.84^a	0.85^a	0.86^a	0.86^a	0.83^a	0.84^a	0.85^a	0.85^a	0.84^a	-0.1^a	0.28^a	0	0.06^b	0.02	-0.01	0.69^a
5	Avg. intb. contagion loss to reg. capital (%)					1	0.98^a	0.98^a	0.96^a	1^a	0.99^a	0.98^a	0.96^a	0.8^a	-0.12^a	0.34^a	-0.04	0.01	0.01	0.04	0.84^a
6	VaR 95% of intb. contagion loss to reg. capital (%)						1	1^a	0.98^a	0.98^a	1^a	1^a	0.99^a	0.8^a	-0.11^a	0.34^a	-0.02	0	-0.01	0.03	0.86^a
7	E.S. at 95% of intb. contagion loss to reg. capital (%)							1	0.99^a	0.97^a	0.99^a	1^a	0.99^a	0.8^a	-0.1^a	0.34^a	-0.02	0	0	0.03	0.86^a
8	Max of intb. contagion loss to reg. capital (%)								1	0.96^a	0.98^a	0.99^a	1^a	0.8^a	-0.1^a	0.34^a	-0.01	0	0	0.02	0.86^a
9	Avg. of intb. contagion loss to RWAs (%)									1	0.98^a	0.98^a	0.96^a	0.79^a	-0.12^a	0.33^a	-0.05^c	0	0.01	0.05^b	0.84^a
10	VaR 95% of intb. contagion loss to RWAs (%)										1	1^a	0.98^a	0.8^a	-0.11^a	0.34^a	-0.03	-0.01	0	0.04^c	0.86^a
11	E.S. at 95% of intb. contagion loss to RWAs (%)											1	0.99^a	0.8^a	-0.11^a	0.34^a	-0.03	-0.01	0	0.04^c	0.87^a
12	Max. of intb. contagion loss to RWAs (%)												1	0.8^a	-0.1^a	0.34^a	-0.03	-0.01	0	0.04	0.87^a
13	Avg. NBF													1	-0.05^b	0.32^a	-0.04	0.09^a	0.06^b	0	0.64^a
14	Avg. SBF														1	-0.13^a	-0.02	0.11^a	0.05^c	-0.04	-0.18^a
15	Bank-level Lerner index															1	0.04^c	0.14^a	0.01	-0.08^a	0.36^a
16	Asset-weighted aggregate Lerner index*																1	0.39^a	-0.26^a	-0.73^a	-0.03
17	Unweighted aggregate Lerner index*																	1	0.05^c	-0.67^a	-0.02
18	Boone indicator*																		1	0.36^a	0.03
19	HHI based on bank's total assets*																			1	0.05^b
20	Mkt. shr. based on bank's assets* (%)																				1

Source: Banco de México, authors' calculations.

Notes: a (b) [c] significant at 1% (5%) [10%] level (two-sided test). This Table reports the pairwise Pearson correlation matrix between systemic risk and competition measures. Definitions of variables are in Table A1 in Appendix A.

*For completeness, this Table includes variables used in our robustness test.

Table A3: Correlation matrix between bank-level and macroeconomic control variables and competition variables

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Total assets	1	-0.19^a	0.05^c	-0.13^a	-0.39^a	-0.19^a	0.06^b	-0.04	0.55^a	0.08^a	0.11^a	-0.01	-0.12^a	0.74^a
2	Loans to non-financial private sector to Assets		1	0.63^a	0.58^a	-0.14^a	0.84^a	-0.01	0.05^b	-0.14^a	0.1^a	-0.01	-0.09^a	-0.11^a	-0.02
3	Retail funding			1	0.53^a	-0.11^a	0.54^a	0.01	0.03	0.01	0.08^a	0	-0.07^b	-0.09^a	0.1^a
4	Provision Ratio				1	-0.09^a	0.57^a	0.01	0	-0.08^a	0.03	0.05^b	0.03	-0.05^b	-0.07^a
5	Capital adequacy ratio (%)					1	-0.13^a	-0.02	-0.02	-0.09^a	-0.05^c	-0.03	0	0.05^b	-0.14^a
6	Average risk weight						1	-0.01	0.05^b	-0.07^a	0.1^a	-0.01	-0.07^a	-0.1^a	0.05^c
7	Indicator of economic activity (YoY %)							1	-0.47^a	0.05^b	0.19^a	0.4^a	0.03	-0.38^a	0
8	Inflation (%)								1	-0.06^b	-0.09^a	-0.5^a	0.03	0.18^a	0
9	Bank-level Lerner index									1	0.04^c	0.14^a	0.01	-0.08^a	0.36^a
10	Weighted aggregate Lerner index										1	0.39^a	-0.26^a	-0.73^a	-0.03
11	Unweighted aggregate Lerner index											1	0.05^c	-0.67^a	-0.02
12	Boone indicator												1	0.36^a	0.03
13	HHI based on bank's total assets													1	0.05^b
14	Market share based on bank's assets (%)														1

Source: Banco de México, authors' calculations.
Notes: a (b) [c] significant at 1% (5%) [10%] level (two-sided test). This Table reports the pairwise Pearson correlation matrix between our set of exogenous variables. This set comprises competition variables as well as bank-level and macro controls. Definitions of variables are in Table A1 in Appendix A.

Table A4: Summary statistics with failure threshold of 10.5% CAR

Variable	Mean	Std Dev	Min.	Q. 25	Median	Q. 75	Max
Dependent variables							
Systemic risk/stability measures							
Avg. failed bank assets to sum of assets (%)	0.75	1.92	0.00	0.00	0.02	0.37	20.32
VaR (95%) failed bank assets to sum of assets (%)	1.71	3.86	0.00	0.00	0.00	1.46	42.94
E.S (95%) failed bank assets to sum of assets (%)	2.05	4.45	0.00	0.00	0.02	1.83	46.03
Maximum failed bank assets to sum of assets (%)	2.71	5.52	0.00	0.00	0.26	2.75	53.97
Avg. interbank loss to regulatory capital (%)	1.24	2.54	0.00	0.05	0.20	1.07	16.30
VaR (95%) interbank loss to regulatory capital (%)	2.22	4.19	0.00	0.08	0.38	2.32	38.62
E.S. (95%) interbank loss to regulatory capital (%)	2.54	4.65	0.00	0.10	0.49	2.79	42.16
Maximum interbank loss to regulatory capital (%)	3.02	5.42	0.00	0.12	0.60	3.41	45.29
Avg. interbank loss to RWAs (%)	0.20	0.41	0.00	0.01	0.03	0.17	2.70
VaR (95%) interbank loss to RWAs (%)	0.35	0.68	0.00	0.01	0.06	0.37	6.29
E.S. (95%) interbank loss to RWAs (%)	0.41	0.75	0.00	0.02	0.08	0.44	6.87
Maximum interbank loss to RWAs (%)	0.48	0.87	0.00	0.02	0.09	0.54	7.38
Avg. interbank NBF	0.95	1.83	0.00	0.00	0.08	1.11	19.54
Avg. interbank SBF	0.95	1.83	0.00	0.00	0.08	1.11	19.54
Individual risk/stability measures							
Z-score	50.83	44.74	0.33	20.04	37.81	68.07	328.57
Non-performing loan ratio (%)	3.26	5.18	0.00	0.92	2.09	3.49	31.67
Explanatory variables							
Competition measures							
Bank-level Lerner index	0.20	0.17	-0.71	0.11	0.20	0.31	0.70
Asset-weighted aggregate Lerner index	0.31	0.03	0.23	0.30	0.31	0.33	0.34
Unweighted aggregate Lerner index*	0.19	0.02	0.13	0.18	0.19	0.21	0.25
Boone indicator*	-0.08	0.02	-0.14	-0.10	-0.08	-0.07	-0.04
HHI based on bank's total assets*	1277.50	136.31	1130.11	1174.62	1210.00	1444.07	1552.76
Market share based on bank's assets* (%)	2.71	5.22	0.00	0.23	0.56	1.56	26.48
Bank-level controls							
Bank size (Total assets)[1]	168.39	332.75	0.34	13.20	32.24	110.88	2035.34
Loans to non-financial private sector to assets	0.38	0.26	0.00	0.16	0.36	0.58	0.94
Retail funding to total liabilities	0.49	0.28	0.00	0.26	0.52	0.70	0.99
Provision to assets ratio	0.02	0.03	0.00	0.01	0.01	0.03	0.17
Capital adequacy ratio (%)	23.08	27.34	10.46	14.31	16.29	20.59	463.08
Average risk weight	0.62	0.28	0.05	0.41	0.59	0.77	1.77
Macroeconomic controls							
Global indicator of economic activity (YoY %)	1.99	2.55	-7.92	1.60	2.43	3.24	6.75
Inflation (%)	4.21	1.08	2.27	3.46	4.10	4.91	6.59

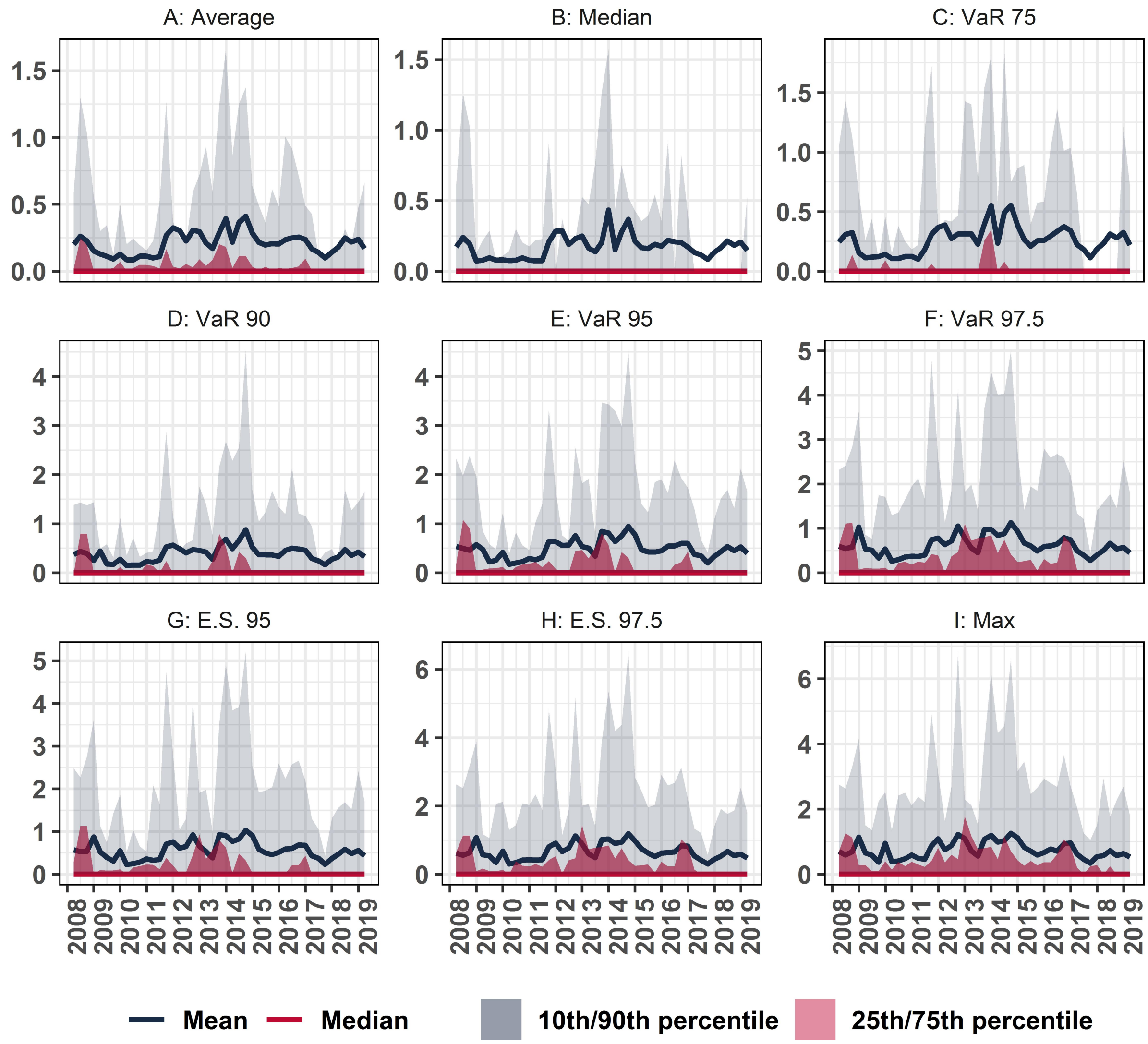
Source: Banco de México, authors' calculations.

Notes: This Table reports summary statistics for the dependent and independent variables used in our robustness test section. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. The data covers the period from March 2008 to March 2019 at quarterly frequency. Our panel is unbalanced and it has 46 banks observed over 45 quarters. The total size of the sample available for estimation purposes is 1,630. In our sample period, two small banks exited as a result of merger and acquisition. Originally, there were 34 banks in the first period. Ten banks received a license to operate over this period and we created two new bank entities as a result of the two mergers and acquisition. Capital refers to bank's regulatory capital (i.e., tier 1 plus tier 2). NBF refers to the number of banks that fail as a consequence of each idiosyncratic bank failure, whereas SBF refers to the number of times that a specific bank fails as a consequence of the idiosyncratic failure, as defined in section 3.3.

[1] Total assets units are in thousands of millions of Mexican pesos. The definition of U.S. billions differs from the one used in Mexico. In US a billion is equal to a thousand million (i.e., 1,000,000,000), whereas in Mexico a billion is equal to a million million (i.e., 1,000,000,000,000).

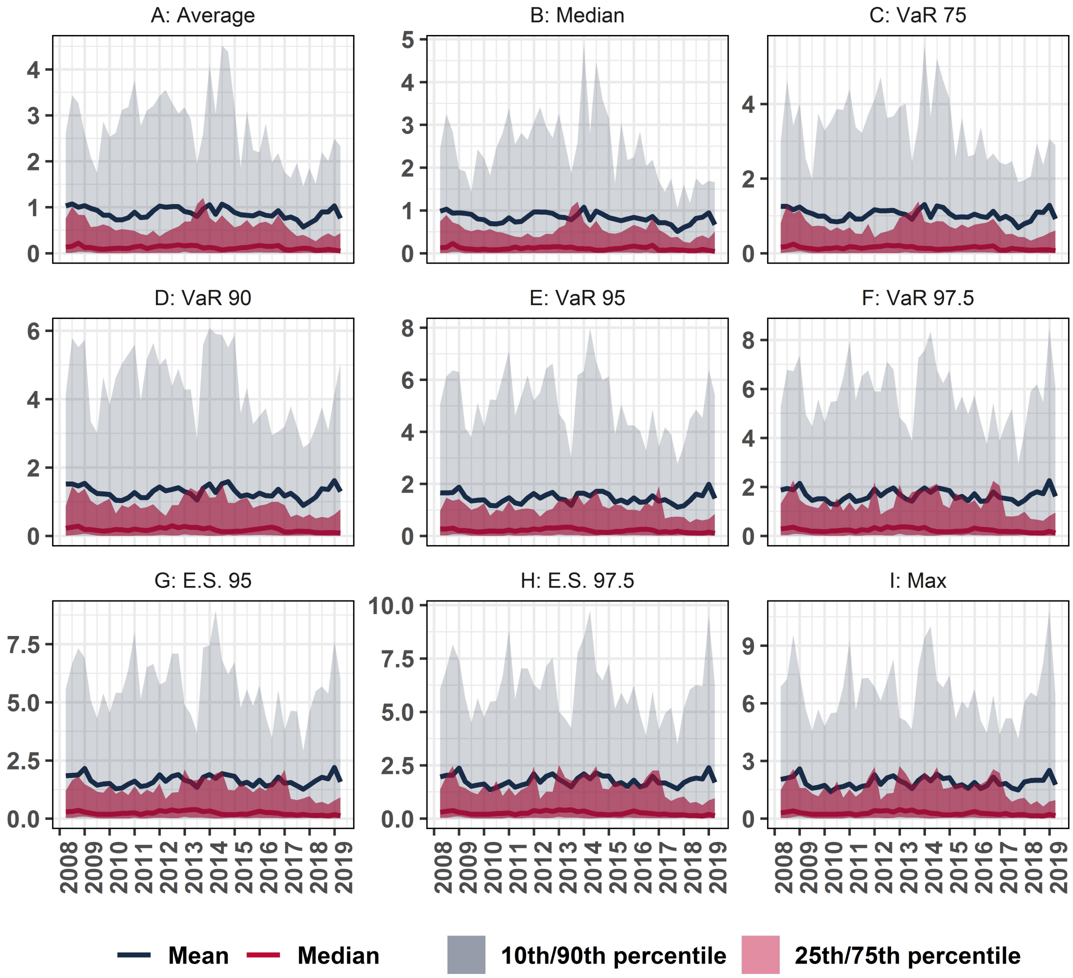
*For completeness, this Table includes variables used in our robustness test.

Figure A1: Evolution of failed bank assets to sum of assets over time: 2008Q1-2019Q1



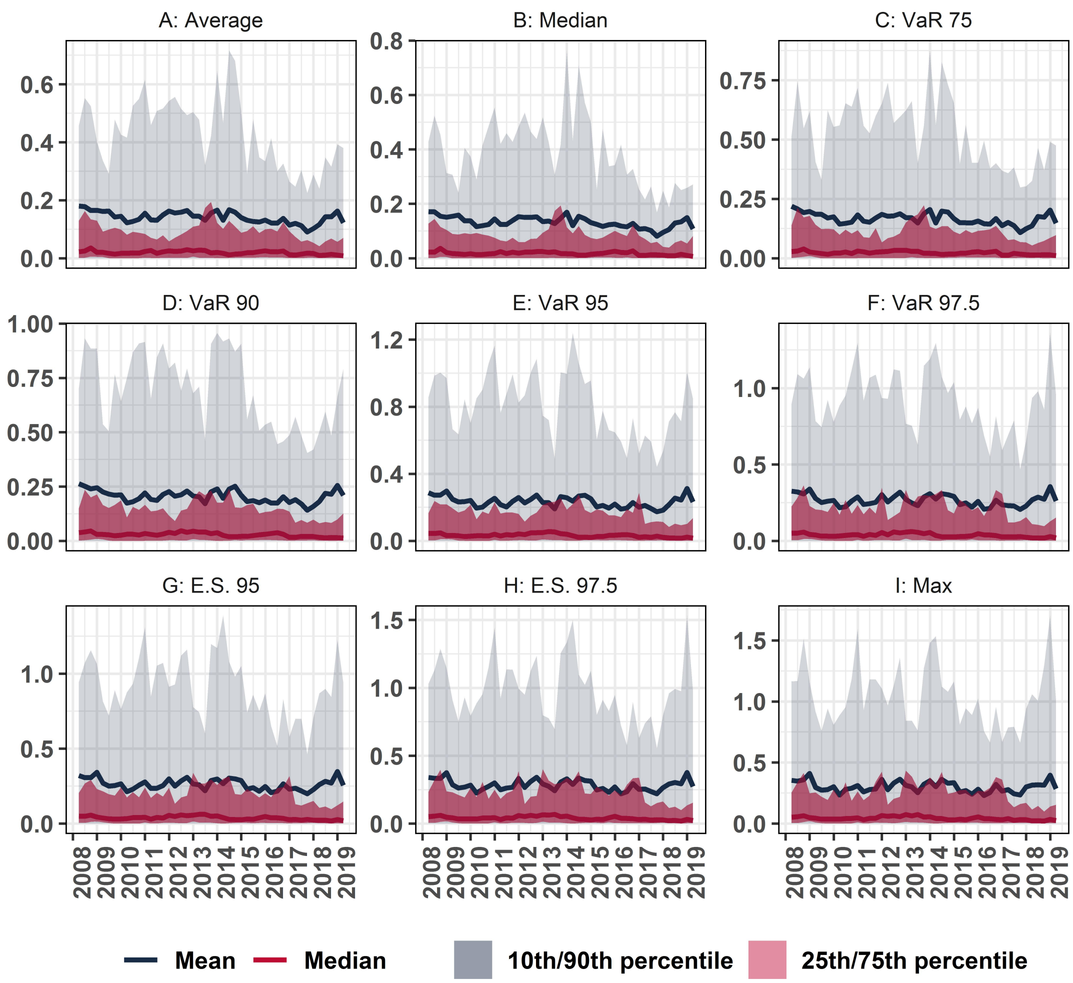
Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of different statistics related to the quarterly empirical distribution of interbank failed assets to sum of assets. This is one of our primary bank-level systemic risk indicators and it is generated using the sequential default algorithm on the banking network of interbank exposures. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. The solid blue and red line show the mean and median value of the distribution, respectively. In each panel, we report the evolution of a different statistic. Panel A to I report the mean, median, VaR (75%), VaR (90%), VaR(95%), VaR(97.5%), E.S. (95%), E.S. (97.5%), and Maximum value, respectively. The pink-shaded area marked '25th/75th percentiles' shows the interval between the 25th and 75th percentile of the distribution. In turn, the gray-shaded area marked '10th/90th percentiles' shows the interval between the 10th and 90th percentile of the distribution. The labels on the horizontal axes indicate the end of the year. Data are available from January 2008 to March 2019.

Figure A2: Evolution of interbank losses as percentage of the sum of banking sector regulatory capital over time: 2008Q1-2019Q1



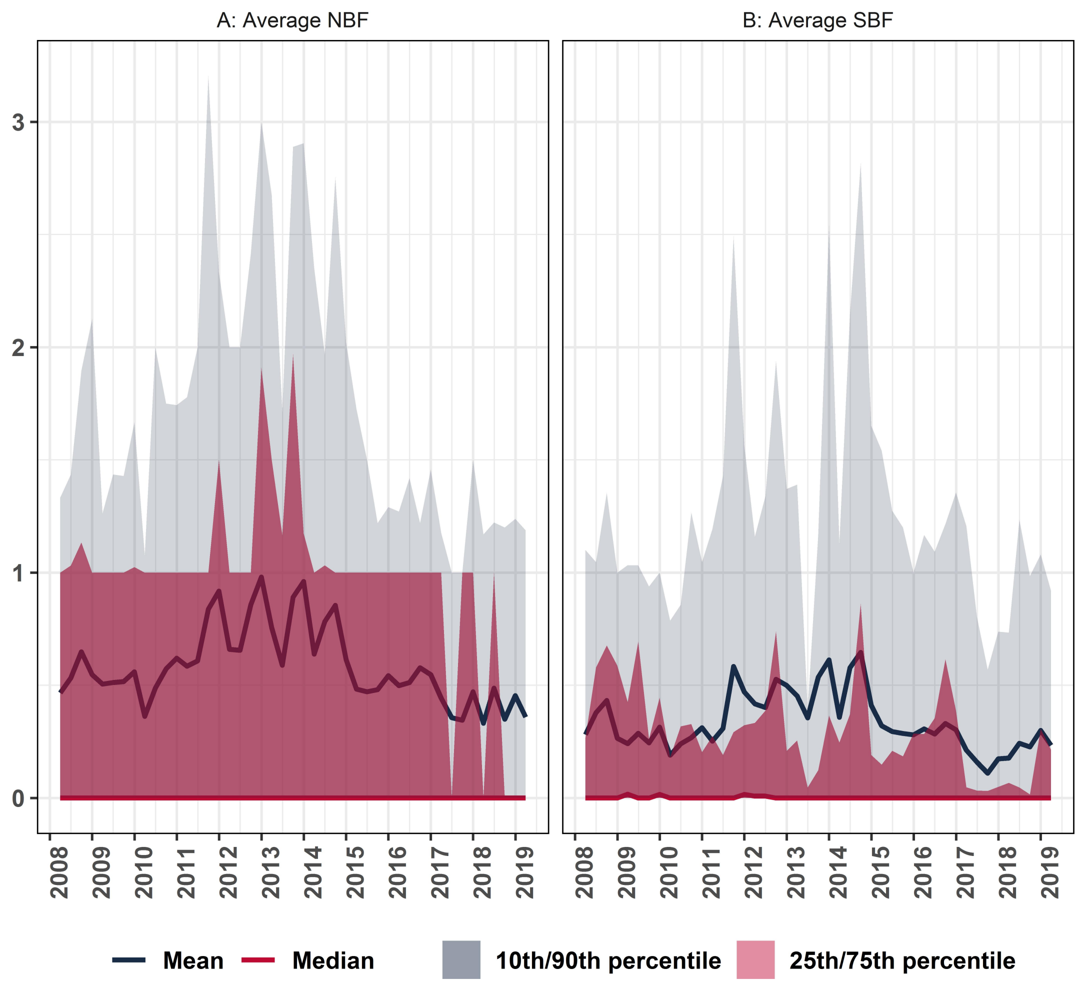
Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of different statistics related to the quarterly empirical distribution of interbank losses as a percentage of the banking sector regulatory capital. This is one of our primary bank-level systemic risk indicators and it is generated using the sequential default algorithm on the banking network of interbank exposures. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. The solid blue and red line show the mean and median value of the distribution, respectively. In each panel, we report the evolution of a different statistic. Panel A to I report the mean, median, VaR (75%), VaR (90%), VaR(95%), VaR(97.5%), E.S. (95%), E.S. (97.5%), and the Maximum value, respectively. The pink-shaded area marked '25th/75th percentiles' shows the interval between the 25th and 75th percentile of the distribution. In turn, the gray-shaded area marked '10th/90th percentiles' shows the interval between the 10th and 90th percentile of the distribution. The labels on the horizontal axes indicate the end of the year. Data are available from January 2008 to March 2019.

Figure A3: Evolution of interbank losses as percentage of the banking sector sum of risk-weighted assets over time: 2008Q1-2019Q1



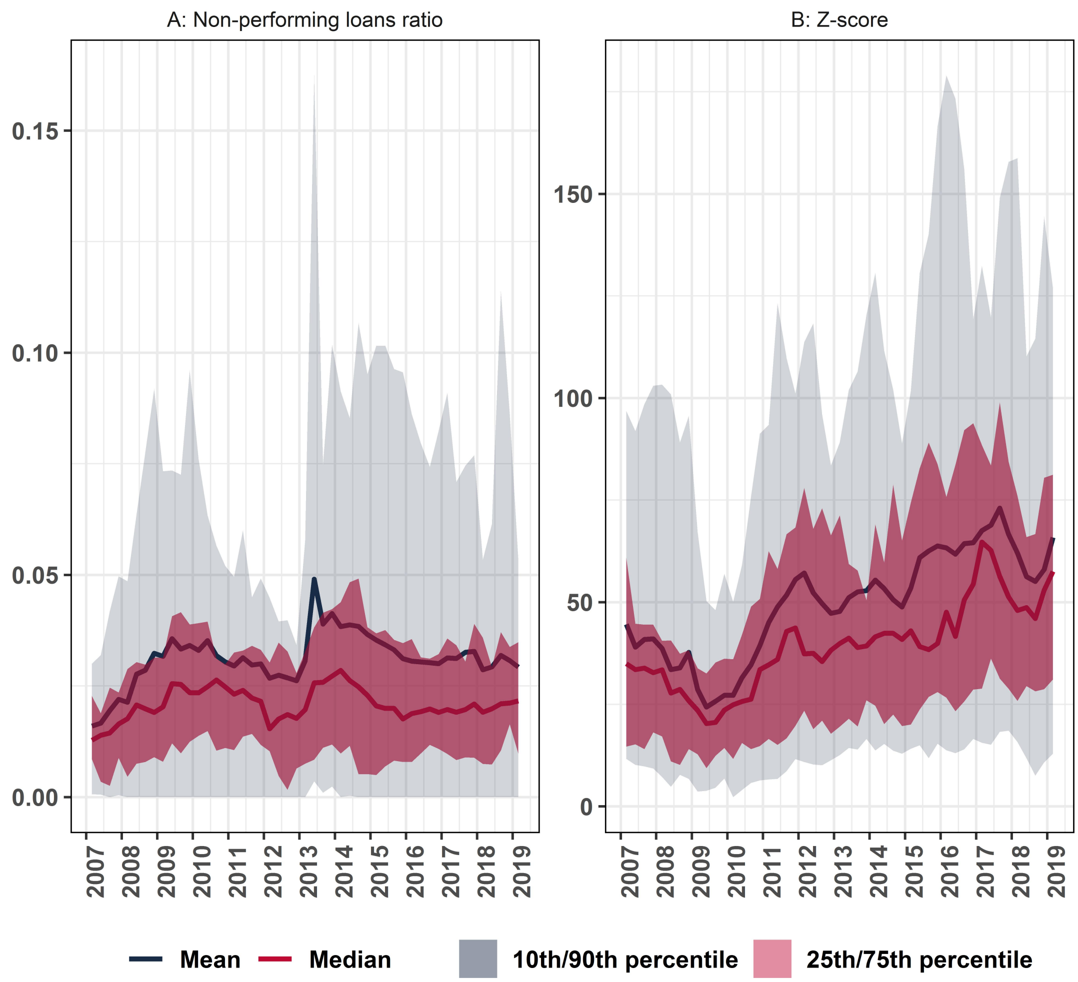
Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of different statistics related to the quarterly empirical distribution of interbank losses as a percentage of risk-weighted assets. This is one of our primary bank-level systemic risk indicators and it is generated using the sequential default algorithm on the banking network of interbank exposures. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. The solid blue and red line show the mean and median value of the distribution, respectively. In each panel, we report the evolution of a different statistic. Panel A to I report the mean, median, VaR (75%), VaR (90%), VaR(95%), VaR(97.5%), E.S. (95%), E.S. (97.5%), and the Maximum value, respectively. The pink-shaded area marked '25th/75th percentiles' shows the interval between the 25th and 75th percentile of the distribution. In turn, the gray-shaded area marked '10th/90th percentiles' shows the interval between the 10th and 90th percentile of the distribution. The labels on the horizontal axes indicate the end of the year. Data are available from January 2008 to March 2019.

Figure A4: Evolution of secondary bank-level systemic risk measures over time: 2008Q1-2019Q1



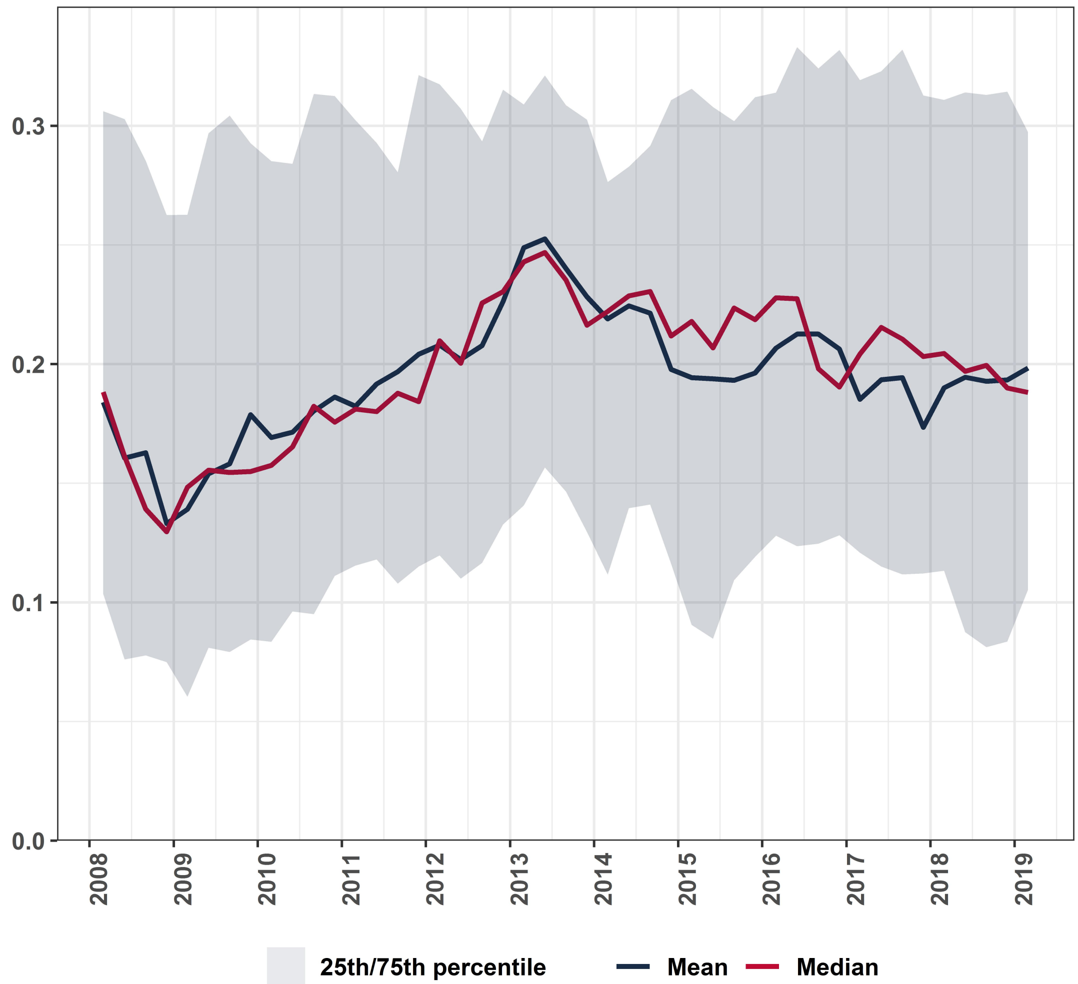
Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of different statistics related to the quarterly empirical distribution of our secondary systemic risk measures: Average NBF and Average SBF. NBF refers to the number of banks that fail as a consequence of each idiosyncratic bank failure, whereas SBF refers to the number of times that a specific bank fails as a consequence of the idiosyncratic failure, as defined in section 3.3. These are the two secondary bank-level systemic risk indicators, which are generated using the sequential default algorithm on the banking network of interbank exposures. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. The blue and red line show the mean and median value of the distribution, respectively. In each panel, we report the average of both indicators. The pink-shaded area marked '25th/75th percentiles' shows the interval between the 25th and 75th percentile of the distribution. In turn, the gray-shaded area marked '10th/90th percentiles' shows the interval between the 10th and 90th percentile of the distribution. The labels on the horizontal axes indicate the end of the year. Data are available from January 2008 to March 2019.

Figure A5: standalone risk measures over time: 2008Q1-2019Q1



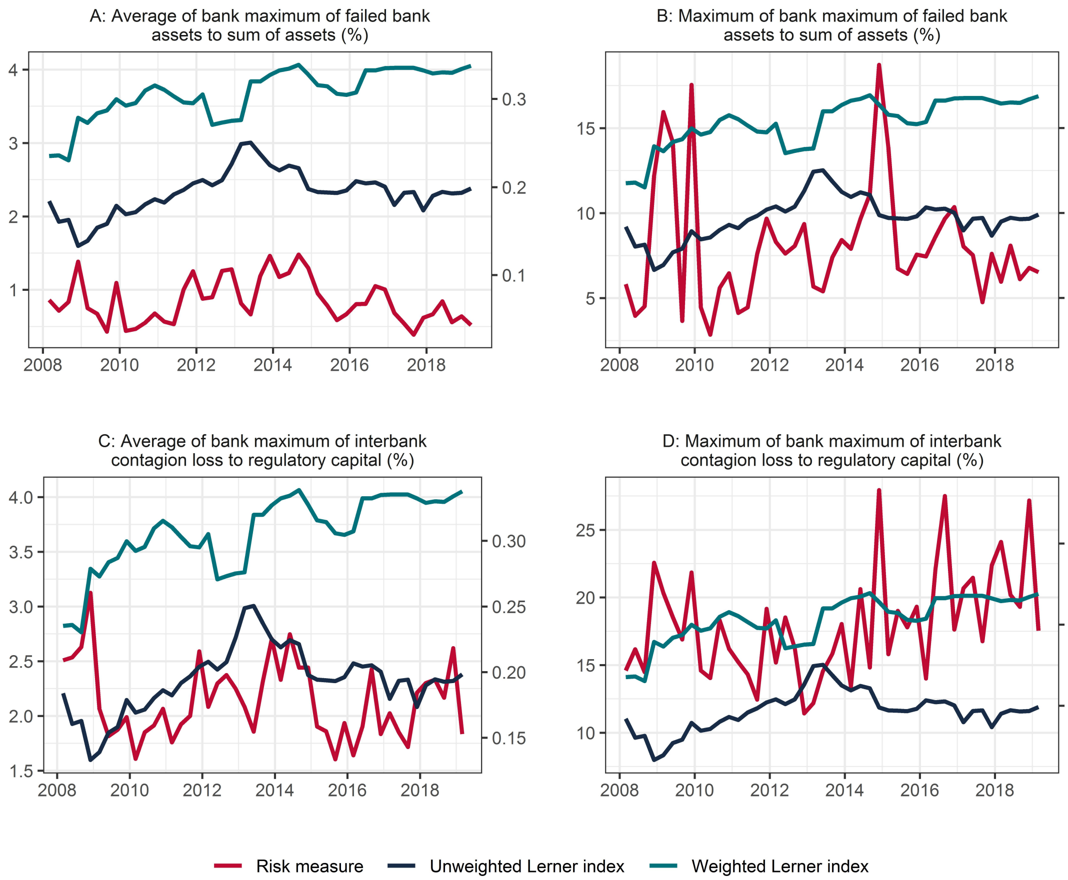
Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of the distribution of our bank-level standalone risk measures. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. Panel A reports the distribution of the non-performing loans ratio (i.e., NPL), whereas Panel B reports the distribution of the Z-score. The blue and red line show the mean and median value of the distribution, respectively. The pink-shaded area marked '25th/75th percentiles' shows the interval between the 25th and 75th percentile of the distribution. In turn, the gray-shaded area marked '10th/90th percentiles' shows the interval between the 10th and 90th percentile of the distribution. The labels on the horizontal axes indicate the end of the year. Data are available from January 2008 to March 2019.

Figure A6: Evolution of the bank-level Lerner index over time: 2008Q1-2019Q1



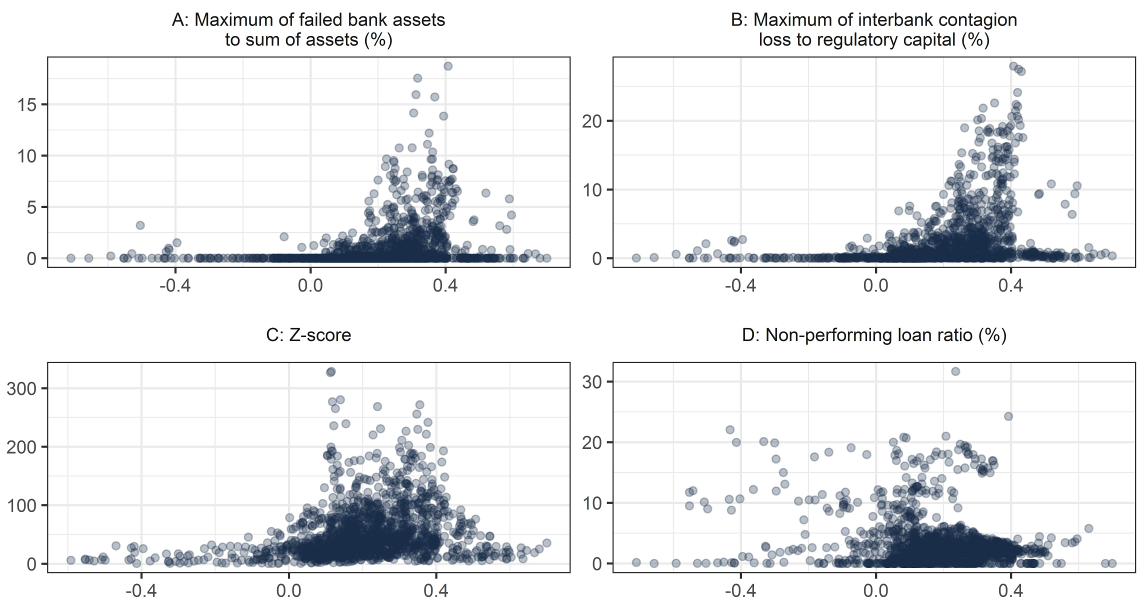
Source: Banco de México, authors' calculations.
Notes: This Figure shows the quarterly evolution of the bank-level Lerner index over the period from January 2008 to March 2019. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. The solid blue and red line show the mean and median value of the bank-level Lerner distribution, respectively. The shaded area marked as '25th/75th percentile' shows the interval between the 25th and 75th percentile of the distribution. An increase of the Lerner Index indicates an increase in banks market power and this is associated with a decrease in competition. The labels on the horizontal axis indicate the beginning of the year.

Figure A7: Evolution of two primary bank-level systemic risk and competition measures over time: 2008Q1-2019Q1.



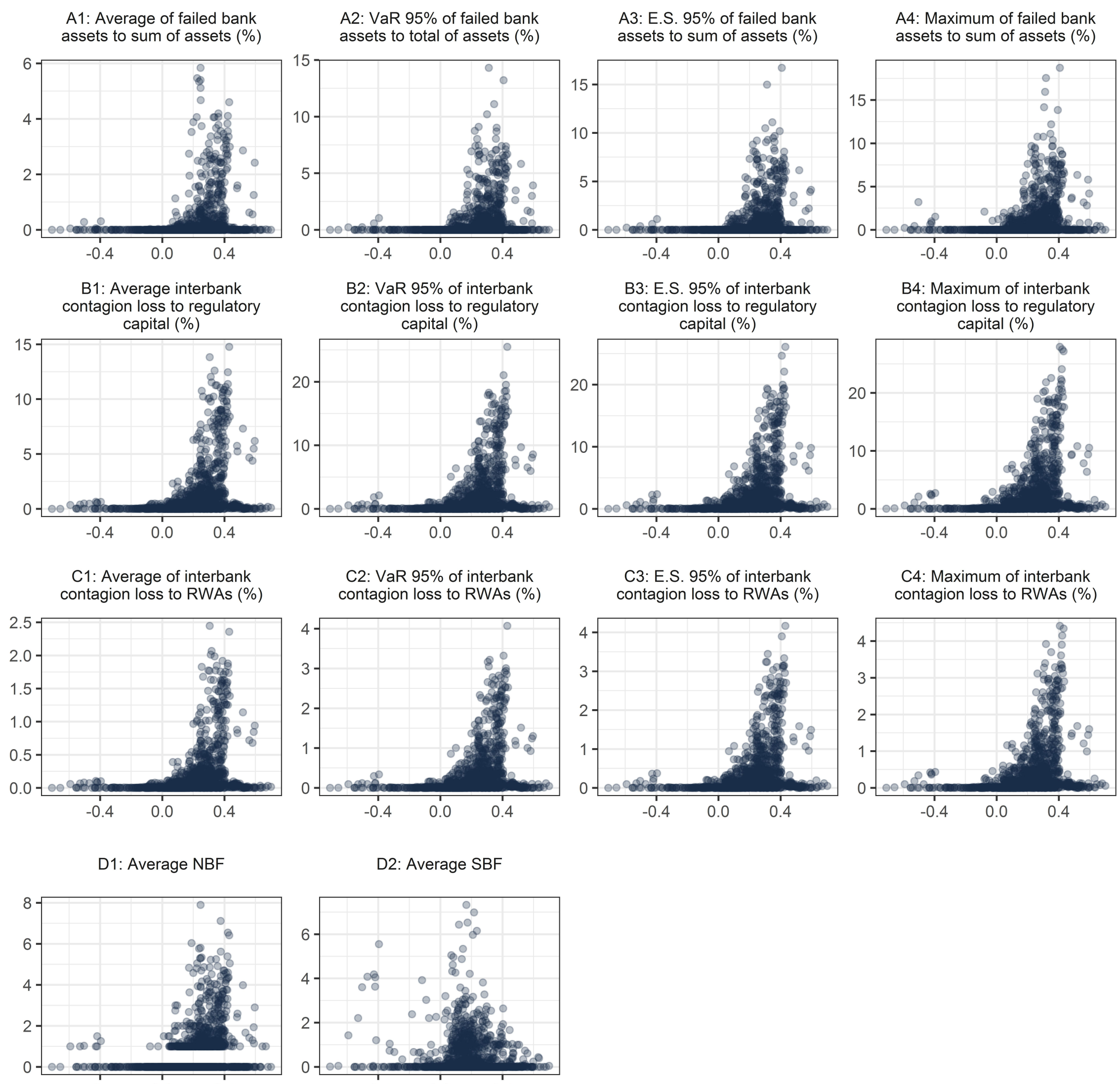
Source: Banco de México, authors' calculations.
Notes: This Figure shows the quarterly evolution of two primary bank-level systemic risk measures (solid red line) and the bank-level (solid dark blue line) and weighted aggregate (solid light blue line) Lerner indices. The two primary bank-level systemic risk measures are failed bank assets to sum of assets and maximum of interbank contagion loss to banking sector regulatory capital. Systemic risk indicators are measured on the left vertical axis, whereas the bank-level & weighted aggregate Lerner index are both measured on the right axis for the period 2008 to 2019. Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. Panel A shows the evolution of the average of bank-level maximum failed bank assets to sum of assets. Panel B shows the evolution of the maximum of bank-level maximum failed bank assets to sum of assets. Panel C shows the evolution of the average of the bank-level maximum of interbank contagion loss to banking sector regulatory capital. Panel D shows the evolution of the maximum of the bank-level maximum of interbank contagion loss to banking sector regulatory capital. Bank-level systemic risk variables are defined in section 3.3.1. The two competition measures are defined in section 3.2.3.1. The labels on the horizontal axis indicate the end of the year.

Figure A8: Scatter diagram between bank-level systemic risk measures and bank-level Lerner index over time: 2008Q1-2019Q1



Source: Banco de México, authors' calculations.
Notes: This Figure shows a scatter plot for a subset of bank-level systemic and standalone risk measures (measured on the left vertical axis) in relation to the bank-level Lerner index (measured on the horizontal axis). Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. Each dot is a bank-level combination between the systemic or standalone risk and the Lerner index competition value. Panel A shows the scatter diagram between the bank-level maximum of failed bank assets to sum of assets (vertical axis) to the bank-level Lerner index (horizontal axis). Panel B shows the scatter diagram between the bank-level maximum of interbank contagion loss to sum of banking sector regulatory capital (vertical axis) to the bank-level Lerner index (horizontal axis). Panel C shows the scatter diagram between the bank-level Z-Score (vertical axis) to the bank-level Lerner index (horizontal axis). Panel D shows the scatter diagram between the bank-level non-performing loans ratio (vertical axis) to the bank-level Lerner index (horizontal axis). Data are available from January 2008 to March 2019.

Figure A9: Pairwise scatter diagram between bank-level systemic risk measures and the bank-level Lerner index over time: 2008Q1-2019Q1



Source: Banco de México, authors' calculations.
Notes: This Figure reports pairwise scatter diagrams to assess whether the strength and sign of the association between systemic risk measures (measured on the left vertical axis) and the bank-level Lerner index (measured on the horizontal axis). Definitions of variables are in Table A1 in Appendix A and in section 3.3 we provide additional details for all variables. Each dot is a bank-level combination between the systemic risk and the Lerner index competition value. Panel A1 to A4 comprises four statistics (i.e., Mean, VaR(95%), E.S.(95%), Maximum) for failed bank assets to total assets. Panel B1 to B4 comprises four statistics (i.e., Mean, VaR(95%), E.S.(95%), Maximum) for interbank contagion loss to the sum of banking sector regulatory capital. Panel C1 to C4 comprises four statistics (i.e., Mean, VaR(95%), E.S.(95%), Maximum) for average of interbank contagion loss to banking sector sum of risk-weighted assets (RWAs). Panel D1 and D2 show the evolution of the average value of our two bank-level secondary systemic risk measures: NBF and SBF. NBF refers to the number of banks that fail as a consequence of each idiosyncratic bank failure, whereas SBF refers to the number of times that a specific bank fails as a consequence of the idiosyncratic failure, as defined in section 3.3. Data are available from January 2008 to March 2019.

Appendix B

In this appendix, we show the results of our robustness tests (see section 4.3 of our paper). In particular, we consider the following six robustness tests:

1. Baseline model including supplementary risk statistics (see Table B1 and B2)
2. Use of alternative competition proxy measures, such as the Boone indicator, the Herfindahl Hirschmann index and the bank's market share (see Table B3 to B5).
3. Use of monthly data (see Table B6).
4. Baseline model assuming that a bank failure occurs when any bank's capital adequacy ratio falls below the 10.5 percent threshold (see Table B7).
5. Baseline model excluding investment banks from sample (see Table B8).
6. Baseline model using one step GMM approach (see Table B9).

B1 Supplementary systemic risk statistics

The worst contagion chain is the most common and well-known measure in network theory that is used to analyze direct contagion risk in interbank markets (Upper (2011)). In our robustness exercises, we also report the mean, value-at-risk (VaR), expected shortfall (E.S.), or conditional value-at-risk (CVaR), along with the maximum value. All in all, this approach leads to twelve primary variables. Moreover, as a supplement, we also compute two secondary systemic risk measures at the bank level: (i) for each point in time t, the number of banks that fail as a consequence of each idiosyncratic bank failure (NBF), and (ii) for each point in time t, the number of times that a specific bank fails as a consequence of the idiosyncratic failure (SBF) of any other bank. The two secondary systemic risk measures capture a bankruptcy frequency dimension rather than bankruptcy severity in terms of contagion loss. Hence, we re-estimated our baseline model (eq.(2)) using as dependent variables these supplementary measures. Table B1 and B2 in Appendix B show the results for our estimations including and excluding control variables, respectively. Each Table has fourteen columns, and these vary depending on the dependent bank-level systemic risk variable being analyzed. In Columns (1) to (4) of Table B1 and B2, we analyze bank-level failed bank assets to sum of assets. In turn, Columns (5) to (8) and Columns (9) to (12) of Table B1 and B2 present the results for interbank contagion loss to regulatory capital and interbank contagion loss to RWAs, respectively. Finally, Columns (13) and (14) of Table B1 and B2 show our two secondary bank-level proxy variables for systemic risk, namely, NBF and SBF. We find that the relationship between the bank-level Lerner index and systemic risk variable is both negative and statistically significant at least at the 10 percent level, except for a few cases. As expected, the size or magnitude of the coefficient increases in absolute value as we move progressively away from the average to consider systemic risk tail measures (i.e., VaR, CVaR, and maximum).

B2 Alternative competition measures

Common practice in this literature is to use alternative measures of competition for robustness test purposes. However, the literature fails to distinguish properly between the nature of the measures computed at the sector level from those available at the individual or bank level. In our view, this is a source of misunderstanding because a bank's systemic importance is a driving factor that largely affects the nature of the relationship between banks' competition and risk measures. To assess the degree of robustness of our measures compared with alternative competition indicators and to overcome its omission, we use two alternative sector-level measures: (i) Boone indicator; and (ii) HHI concentration index as measured by the bank's market share based on total assets. We also employ a bank-level measure: a bank's market shares based on total assets.[49]

The estimation of the Boone indicator follows Schaeck and Cihák (2014) and Bátiz-Zuk and Lara-Sánchez (2022). A brief description is available in Appendix D, and Figure D1 shows the evolution of the Boone indicator. The Boone indicator is a sector-level variable and is more volatile than other measures of competition (see de Ramon and Straughan (2020) and Bátiz-Zuk and Lara-Sánchez (2022)). Moreover, an increase in the Boone indicator signals that there is less intense competition in the banking sector as a whole. Table B3 in Appendix B shows the regression results for the Boone indicator, for which we include all bank characteristics and macroeconomic control variables. As expected, tail measures for our three primary

[49]Claessens and Laeven (2004) show that concentration measures may be a very poor proxy of competition. Notwithstanding this statement, common practice is to use these indicators in this strand of the literature for robustness purposes (Anginer et al. (2014)).

systemic risk variables and the two secondary systemic risk proxies[50] show that a negative linear relationship exists with the Boone indicator at the 5 percent level. No rejection of the Hansen J test suggests that the chosen instruments are valid. Overall, this result reinforces the previous finding that a negative relationship exists between the level of market power and systemic risk.

Table B4 in Appendix B shows the results for HHI based on a bank's total assets. We find that 13 out of 14 systemic risk measures have a negative linear relationship with the HHI at the 10 percent level. No rejection of the Hansen J test suggests that the chosen instruments are valid. Overall, this result reinforces the previous finding that there is a negative relationship between competition and systemic risk. This result should be taken with prudence because Claessens and Laeven (2004) showed that bank concentration is not a good proxy of the bank's competitive environment. Moreover, for some of the systemic risk measures, the AR(2) statistic is not valid.

Finally we calculate market shares to track how a bank's asset share evolves. Panels A and B of Figure D2 in Appendix D show the evolution of HHI and bank's market shares, respectively. We refer interested readers to Bátiz-Zuk and Lara-Sánchez (2022) (or to de Ramon and Straughan (2020)) for a review and application of these metrics to the Mexican (UK) banking sector. Table B5 in Appendix B shows the results for bank-level market shares based on total assets. As before, tail measures for our three primary systemic risk variables and one out of the two secondary systemic risk proxies[51] show that a negative linear relationship exists with the bank's asset market share at the 5 percent level. This result suggests that an increase in an individual bank's asset market share decreases systemic risk.

B3 Estimations using monthly data

It is interesting to use a finer time frequency because bank-level systemic risk measures may have wide variations across different time intervals. Bátiz-Zuk and Lara-Sánchez (2022) show how to use monthly data to assess the evolution of competition measures. Using monthly data leads to a change in the estimation method. When we use monthly data, we are in a situation in which the length of the time dimension (T) is longer than the number of N cross-sections

[50]See Columns (2) to (4), (7) to (8), and (11) to (14) of Table B3 in Appendix B.
[51]See Columns (2) to (4), (6) to (8), and (10) to (13) of Table B5 in Appendix B.

(i.e., $T > N$). In this setting, the Arellano-Bond estimator is not the best choice (see Roodman (2009a)) because it requires that the number of cross sections be greater than the number of periods of the time dimension (i.e., $N > T$). To circumvent this limitation, we use a static instrumental panel approach based on a two-step GMM technique. We estimate eq.(2) excluding the lagged dependent variable and use a static panel model including all variables to assess whether a change in the time frequency modifies the sign, size, or statistical significance of our coefficients. To estimate the model, we use up to four lags of the competition measures. Additionally, we lag our bank-level control variables by six periods (i.e., two quarters) to be consistent with the lag structure in our baseline model. Table B6 in Appendix B shows the results for the static panel model. Relative to our quarterly estimates, using monthly data for the bank-level Lerner index supports the existence of a negative relationship between systemic risk and competition at the 5 percent level. In this case, support exists for our baseline result, for which increased market power (i.e., a reduction in competition) is associated on average with less bank systemic risk.

B4 Increasing the threshold for the minimum capital adequacy ratio to 10.5 percent

We test what happens when we increase the minimum regulatory capital adequacy ratio from 8 to 10.5 percent. Thus, we stress test our sequential default algorithm, follow an alternative and stricter default criterion and assume that any bank failure occurs earlier than expected by the regulatory framework. Table A4 in Appendix A shows the summary statistics for these systemic risk measures, whereas Table B7 in appendix B displays the results of this robustness test for the bank-level Lerner index. We report that the linear coefficient is negative and significant at the 5 percent level for almost all of the tail measures of our primary systemic risk variables (excluding Columns (2) to (3)), supporting our baseline result that increased market power (i.e., a reduction in competition) is associated on average with less bank systemic risk.

B5 Sample selection criteria: excluding non-traditional bank entities

Next, we investigate what happens if we exclude investment banks from our baseline model sample. Table B8 in Appendix B shows the results for the bank-level Lerner index. As before, our results remain robust to the exclusion of non-traditional bank entities.

B6 Arellano-Bond one step GMM estimation

We estimate eq.(2) using the Arellano and Bond (1991) first difference one step GMM estimator to assess that the significance of our reported coefficients is not the result of downward bias in our estimated standard error (see Windmeijer (2005)). Table B9 shows the result for the one step GMM estimation of our baseline specification using the bank-level Lerner index. As before, a significant linear negative association exists between bank-level Lerner index and systemic risk indicators.

Table B1: Systemic risk and competition: baseline results using bank level Lerner index

	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
Variables	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lagged dep. var.	0.6595***	0.2289***	0.4022***	0.2707***	0.9378**	0.1893	0.0723	-0.0607	0.9694***	0.2594	0.1209	-0.0460	0.1129	0.5769***
	(0.0679)	(0.0626)	(0.0690)	(0.0462)	(0.4133)	(0.1643)	(0.1242)	(0.0870)	(0.3509)	(0.1734)	(0.1308)	(0.0868)	(0.0934)	(0.0957)
Lerner	-0.0151*	-0.0426*	-0.0559**	-0.1061***	-0.0150	-0.0837**	-0.0859***	-0.1237***	-0.0030	-0.0127**	-0.0131***	-0.0190***	-3.7104**	-1.1604*
	(0.0086)	(0.0225)	(0.0281)	(0.0404)	(0.0213)	(0.0338)	(0.0311)	(0.0430)	(0.0033)	(0.0053)	(0.0047)	(0.0067)	(1.4719)	(0.6586)
Obs.	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513	1,513
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(1) p-value	0.0249	0.0356	0.0161	0.0440	0.119	0.0501	0.134	0.180	0.105	0.0299	0.0973	0.162	0.00326	0.0219
AR(2) p-value	0.296	0.916	0.989	0.544	0.956	0.865	0.809	0.784	0.790	0.746	0.892	0.740	0.861	0.540
Hansen J p-value	0.700	0.904	0.977	0.569	0.405	0.787	0.910	0.719	0.777	0.677	0.791	0.617	0.879	0.774

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2) $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m-k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B2: Systemic risk and competition: baseline results using standard Lerner index

Variables	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lagged dep. var.	0.6628***	0.2334***	0.4315***	0.2899***	1.0268**	0.1267	0.0115	-0.0784	1.1062***	0.2113	0.0663	-0.0575	0.1383	0.6542***
	(0.0664)	(0.0654)	(0.0568)	(0.0437)	(0.4601)	(0.1514)	(0.1002)	(0.0748)	(0.3640)	(0.1494)	(0.1018)	(0.0741)	(0.0885)	(0.0671)
Lerner	-0.0123*	-0.0358**	-0.0460**	-0.0901***	-0.0072	-0.0727**	-0.0755***	-0.1076***	-0.0015	-0.0116**	-0.0119***	-0.0168***	-2.9416**	-0.8616*
	(0.0069)	(0.0181)	(0.0223)	(0.0342)	(0.0127)	(0.0320)	(0.0278)	(0.0350)	(0.0019)	(0.0050)	(0.0041)	(0.0054)	(1.2023)	(0.4415)
Bank size (log Assets)	0.0015	0.0046*	0.0067**	0.0131***	0.0005	0.0093**	0.0098**	0.0147***	0.0001	0.0015**	0.0016***	0.0023***	0.5073***	0.3034**
	(0.0010)	(0.0025)	(0.0034)	(0.0048)	(0.0020)	(0.0047)	(0.0042)	(0.0052)	(0.0003)	(0.0007)	(0.0006)	(0.0008)	(0.1754)	(0.1280)
Loan to assets ratio	-0.0005	0.0055	-0.0005	-0.0070	-0.0008	-0.0036	-0.0017	-0.0014	0.0001	-0.0006	-0.0003	-0.0003	0.9759*	0.5589
	(0.0024)	(0.0059)	(0.0068)	(0.0087)	(0.0041)	(0.0065)	(0.0060)	(0.0078)	(0.0006)	(0.0010)	(0.0009)	(0.0012)	(0.5637)	(0.3700)
Retail funding ratio	-0.0001	0.0011	0.0067	0.0103*	0.0019	0.0020	0.0029	0.0064*	0.0004	0.0006	0.0007	0.0012**	-0.0639	-0.0933
	(0.0006)	(0.0025)	(0.0043)	(0.0060)	(0.0021)	(0.0024)	(0.0025)	(0.0036)	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.2068)	(0.1658)
Provision to assets ratio	-0.0262	-0.0509	-0.0460	-0.0338	-0.0053	-0.0250	-0.0107	0.0039	-0.0003	-0.0044	-0.0016	0.0009	-1.1851	-0.7094
	(0.0160)	(0.0336)	(0.0363)	(0.0404)	(0.0263)	(0.0352)	(0.0310)	(0.0367)	(0.0040)	(0.0056)	(0.0049)	(0.0058)	(2.9736)	(1.6099)
Capital adequacy ratio	0.0002	0.0010	0.0009	0.0007	0.0007	0.0012	0.0012	0.0013	0.0001	0.0002	0.0002	0.0002	0.0449	-0.0106
	(0.0006)	(0.0014)	(0.0018)	(0.0022)	(0.0009)	(0.0020)	(0.0021)	(0.0028)	(0.0001)	(0.0003)	(0.0003)	(0.0004)	(0.1276)	(0.0628)
Average risk weight	0.0014	0.0031	0.0022	0.0032	0.0010	0.0037	0.0013	-0.0003	0.0000	0.0008	0.0003	0.0001	-0.5052**	-0.2965
	(0.0016)	(0.0034)	(0.0038)	(0.0037)	(0.0023)	(0.0038)	(0.0031)	(0.0031)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.2139)	(0.2090)
Economic activity	0.0076	0.0312	0.0040	-0.0153	-0.0077	-0.0635**	-0.0670***	-0.0624**	-0.0017	-0.0100**	-0.0104***	-0.0086*	-1.7496	0.5847
	(0.0080)	(0.0194)	(0.0137)	(0.0256)	(0.0149)	(0.0312)	(0.0251)	(0.0280)	(0.0023)	(0.0050)	(0.0039)	(0.0046)	(1.5409)	(0.9997)
Lagged economic activity	0.0004	0.0251	0.0229	0.0429	-0.0112	0.0295	0.0349**	0.0483**	-0.0004	0.0054*	0.0060**	0.0080**	1.2882	-0.1467
	(0.0052)	(0.0174)	(0.0186)	(0.0299)	(0.0121)	(0.0190)	(0.0172)	(0.0241)	(0.0020)	(0.0031)	(0.0027)	(0.0039)	(0.9731)	(0.6232)
Inflation	-0.0602*	-0.0615	-0.0806**	-0.1057**	-0.1063**	-0.1811***	-0.1478***	-0.1638***	-0.0227**	-0.0332***	-0.0262***	-0.0273***	-9.9945**	-9.3935**
	(0.0360)	(0.0440)	(0.0405)	(0.0419)	(0.0481)	(0.0681)	(0.0495)	(0.0535)	(0.0091)	(0.0112)	(0.0079)	(0.0087)	(4.0743)	(3.7278)
Obs.	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0.0001	0	0	0	0	0	0	0	0
AR(1) p-value	0.0246	0.034	0.0123	0.038	0.146	0.102	0.195	0.189	0.122	0.0561	0.139	0.166	0.0026	0.0186
AR(2) p-value	0.3	0.93	0.996	0.564	0.972	0.755	0.262	0.281	0.826	0.99	0.406	0.264	0.915	0.606
Hansen J p-value	0.689	0.869	0.933	0.621	0.249	0.474	0.863	0.933	0.529	0.511	0.957	0.864	0.63	0.895

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m-k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B3: Systemic risk and competition: baseline results using the Boone indicator

	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
Variables	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lagged dep. var.	0.7040***	0.4350**	0.4578***	0.4087***	1.1428***	0.5246*	0.4523*	0.2978	1.1507***	0.5115*	0.4584*	0.3163	0.2832**	0.7002***
	(0.0717)	(0.1881)	(0.1488)	(0.1578)	(0.2696)	(0.2920)	(0.2735)	(0.3449)	(0.2406)	(0.2795)	(0.2405)	(0.3292)	(0.1117)	(0.0724)
Boone	-0.0514	-0.0634**	-0.0803**	-0.1546***	-0.0460	-0.0492	-0.0976**	-0.2011***	-0.0055	-0.0060	-0.0137**	-0.0318***	-13.5589***	-6.7253**
	(0.0355)	(0.0282)	(0.0333)	(0.0539)	(0.0403)	(0.0388)	(0.0414)	(0.0622)	(0.0063)	(0.0064)	(0.0066)	(0.0096)	(3.9893)	(2.9594)
Bank size (log Assets)	0.0003	0.0007	0.0015*	0.0026*	-0.0005	0.0000	0.0009	0.0027	-0.0001	-0.0000	0.0001	0.0004	0.1835	0.0381
	(0.0006)	(0.0008)	(0.0008)	(0.0014)	(0.0006)	(0.0014)	(0.0016)	(0.0021)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.1236)	(0.1070)
Loan to assets ratio	0.0011	0.0066*	0.0070*	0.0053	0.0009	0.0043	0.0033	0.0022	0.0002	0.0007	0.0005	0.0005	0.7048	0.8328**
	(0.0020)	(0.0040)	(0.0042)	(0.0053)	(0.0035)	(0.0045)	(0.0050)	(0.0068)	(0.0006)	(0.0008)	(0.0008)	(0.0011)	(0.6129)	(0.4058)
Retail funding ratio	-0.0015	-0.0013	-0.0027	-0.0046	0.0005	0.0000	0.0012	-0.0007	0.0001	-0.0000	0.0002	-0.0001	-0.1982	-0.4023*
	(0.0010)	(0.0028)	(0.0037)	(0.0043)	(0.0016)	(0.0033)	(0.0038)	(0.0045)	(0.0003)	(0.0006)	(0.0006)	(0.0007)	(0.2513)	(0.2421)
Provision to assets ratio	-0.0093	-0.0291	-0.0250	0.0054	0.0074	-0.0066	0.0141	0.0499	0.0014	-0.0015	0.0018	0.0074	0.6653	-2.2663
	(0.0103)	(0.0243)	(0.0223)	(0.0306)	(0.0248)	(0.0265)	(0.0355)	(0.0550)	(0.0043)	(0.0046)	(0.0059)	(0.0089)	(3.2923)	(1.6729)
Capital adequacy ratio	0.0001	0.0003	0.0002	-0.0013*	0.0006	0.0013	0.0010	0.0004	0.0001	0.0002	0.0002	0.0001	-0.0389	-0.0055
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0011)	(0.0010)	(0.0012)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0757)	(0.0659)
Average risk weight	0.0003	-0.0012	-0.0013	-0.0071	0.0002	0.0026	0.0023	0.0010	0.0000	0.0004	0.0004	0.0001	-0.4735	-0.2329
	(0.0013)	(0.0024)	(0.0023)	(0.0044)	(0.0013)	(0.0028)	(0.0025)	(0.0033)	(0.0002)	(0.0005)	(0.0004)	(0.0005)	(0.3696)	(0.2452)
Economic activity	0.0140	0.0045	0.0011	-0.0058	-0.0057	-0.0445	-0.0341	-0.0060	-0.0002	-0.0059	-0.0040	0.0007	0.4640	1.0262
	(0.0130)	(0.0208)	(0.0233)	(0.0278)	(0.0116)	(0.0348)	(0.0286)	(0.0338)	(0.0018)	(0.0053)	(0.0042)	(0.0053)	(1.9175)	(1.1307)
Lagged economic activity	-0.0138	-0.0108	-0.0183	-0.0453**	-0.0358*	-0.0316**	-0.0375***	-0.0499*	-0.0041	-0.0038*	-0.0046**	-0.0066	-2.7449*	-1.0726
	(0.0122)	(0.0129)	(0.0121)	(0.0194)	(0.0211)	(0.0133)	(0.0132)	(0.0275)	(0.0034)	(0.0023)	(0.0022)	(0.0043)	(1.6535)	(1.8102)
Inflation	0.0138	0.0212	0.0225	0.0262	-0.1105***	-0.1431	-0.1214*	-0.0423	-0.0155**	-0.0190	-0.0161	-0.0032	0.8523	-2.9430
	(0.0468)	(0.0554)	(0.0554)	(0.0679)	(0.0419)	(0.0888)	(0.0688)	(0.0818)	(0.0061)	(0.0131)	(0.0100)	(0.0130)	(5.8136)	(3.8338)
Obs.	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389	1,389
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0	0.0001	0.0799	0	0	0	0.08	0	0
AR(1) p-value	0.046	0.0374	0.0394	0.0632	0.121	0.148	0.0963	0.0996	0.12	0.162	0.104	0.0972	0.0049	0.0208
AR(2) p-value	0.386	0.447	0.267	0.387	0.855	0.479	0.419	0.326	0.81	0.52	0.46	0.329	0.988	0.611
Hansen J p-value	0.149	0.177	0.207	0.216	0.287	0.193	0.157	0.168	0.175	0.168	0.134	0.167	0.129	0.496

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B4: Systemic risk and competition: baseline results using HHI based on asset size

Variables	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lagged dep. var.	0.6212***	0.2081**	0.3937***	0.3089***	0.8547***	0.0397	-0.0601	-0.1314	0.8193***	0.0814	-0.0377	-0.1168	0.2923***	0.6565***
	(0.0737)	(0.0869)	(0.0900)	(0.0470)	(0.1921)	(0.1479)	(0.1675)	(0.1169)	(0.1469)	(0.1297)	(0.1634)	(0.1162)	(0.0715)	(0.0545)
HHI	-0.7327*	-1.9621**	-3.0026**	-5.3566**	-1.4040*	-3.6099**	-3.7946**	-5.3941***	-0.2102*	-0.5570**	-0.6066**	-0.8418***	-281.5727***	-54.6846
	(0.4422)	(0.7854)	(1.1968)	(2.2699)	(0.7938)	(1.5462)	(1.5062)	(1.8429)	(0.1210)	(0.2510)	(0.2573)	(0.3036)	(79.4103)	(38.2982)
Bank size (log Assets)	-0.0003	-0.0001	0.0005	0.0011	-0.0006	-0.0011	-0.0008	-0.0002	-0.0001	-0.0002	-0.0001	-0.0000	-0.0340	0.0769
	(0.0005)	(0.0014)	(0.0019)	(0.0031)	(0.0008)	(0.0021)	(0.0024)	(0.0033)	(0.0001)	(0.0003)	(0.0004)	(0.0005)	(0.1365)	(0.0735)
Loan to assets ratio	0.0017	0.0080	0.0074	0.0090	0.0035	0.0098	0.0099	0.0137	0.0006	0.0014	0.0015	0.0020	1.3192	0.4083
	(0.0031)	(0.0075)	(0.0091)	(0.0138)	(0.0043)	(0.0099)	(0.0108)	(0.0148)	(0.0007)	(0.0015)	(0.0017)	(0.0023)	(0.8374)	(0.4056)
Retail funding ratio	-0.0013	-0.0030	-0.0015	-0.0055	-0.0001	-0.0074	-0.0065	-0.0080	0.0001	-0.0010	-0.0009	-0.0011	-0.7033**	-0.0953
	(0.0014)	(0.0034)	(0.0042)	(0.0072)	(0.0020)	(0.0060)	(0.0063)	(0.0083)	(0.0003)	(0.0009)	(0.0010)	(0.0013)	(0.3524)	(0.2172)
Provision to assets ratio	-0.0157	-0.0254	-0.0295	-0.0159	-0.0090	-0.0255	-0.0250	-0.0135	-0.0015	-0.0039	-0.0040	-0.0022	-2.4959	-0.6909
	(0.0155)	(0.0388)	(0.0521)	(0.0844)	(0.0274)	(0.0581)	(0.0681)	(0.0957)	(0.0044)	(0.0091)	(0.0108)	(0.0149)	(4.9989)	(1.7551)
Capital adequacy ratio	-0.0009	-0.0019	-0.0030	-0.0058	-0.0013	-0.0045	-0.0046	-0.0063	-0.0002	-0.0007	-0.0007	-0.0010	-0.3674	-0.0285
	(0.0010)	(0.0019)	(0.0029)	(0.0049)	(0.0016)	(0.0037)	(0.0039)	(0.0052)	(0.0002)	(0.0006)	(0.0006)	(0.0008)	(0.2496)	(0.0886)
Average risk weight	-0.0012	-0.0026	-0.0053	-0.0117	-0.0035	-0.0078	-0.0088	-0.0139	-0.0005	-0.0011	-0.0013	-0.0021	-1.0720**	-0.3292
	(0.0021)	(0.0033)	(0.0051)	(0.0085)	(0.0028)	(0.0063)	(0.0069)	(0.0096)	(0.0005)	(0.0010)	(0.0011)	(0.0015)	(0.5075)	(0.2135)
Economic activity	0.0334*	0.0789**	0.0930**	0.1562*	0.0183	0.0617	0.0760*	0.1342***	0.0025	0.0095	0.0125*	0.0217***	7.7149**	2.5033
	(0.0201)	(0.0381)	(0.0455)	(0.0820)	(0.0174)	(0.0387)	(0.0392)	(0.0508)	(0.0026)	(0.0062)	(0.0066)	(0.0084)	(3.0401)	(1.5261)
Lagged economic activity	-0.0378	-0.0825**	-0.1351**	-0.2422**	-0.0739*	-0.1636**	-0.1665**	-0.2361***	-0.0098*	-0.0247**	-0.0262**	-0.0364***	-13.5512***	-3.0548
	(0.0237)	(0.0408)	(0.0541)	(0.0971)	(0.0396)	(0.0700)	(0.0674)	(0.0828)	(0.0057)	(0.0113)	(0.0115)	(0.0137)	(4.2034)	(2.4895)
Inflation	-0.0414	-0.0227	-0.0304	-0.0310	-0.1490***	-0.0980***	-0.0615	-0.0498	-0.0248***	-0.0180***	-0.0115*	-0.0095	-9.0434**	-9.0228**
	(0.0330)	(0.0367)	(0.0338)	(0.0492)	(0.0453)	(0.0354)	(0.0389)	(0.0439)	(0.0076)	(0.0061)	(0.0064)	(0.0071)	(4.1802)	(3.8308)
Obs.	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0	0.0461	0.0001	0	0	0.0128	0.0021	0	0
AR(1) p-value	0.0269	0.0186	0.0149	0.044	0.0762	0.0398	0.0714	0.0302	0.0795	0.0414	0.0619	0.0282	0.0012	0.0115
AR(2) p-value	0.176	0.534	0.433	0.0266	0.363	0.0905	0.0389	0.0194	0.437	0.102	0.0417	0.0226	0.291	0.398
Hansen J p-value	0.475	0.615	0.974	0.965	0.984	0.93	0.486	0.607	0.889	0.88	0.476	0.582	0.613	0.889

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the systemic risk measures and the second lag of the competition measure. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B5: Systemic risk and competition: baseline results using bank level market shares based on asset size

	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
Variables	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lagged dep. var.	0.6822***	0.1839*	0.3895***	0.2804***	0.7756***	0.2944***	0.1229	-0.0322	0.7306***	0.3380***	0.1697*	-0.0098	0.1957***	0.6137***
	(0.0545)	(0.0963)	(0.0763)	(0.0474)	(0.1182)	(0.1039)	(0.1117)	(0.0969)	(0.1074)	(0.1013)	(0.1000)	(0.0915)	(0.0734)	(0.0787)
Mket. Shrs.	-0.2475	-0.6604***	-0.9375**	-1.3496***	-0.0038	-0.9979***	-1.3882***	-1.7349***	-0.0002	-0.1658***	-0.2335***	-0.2909***	-96.7983**	-16.9980
	(0.1632)	(0.2181)	(0.3747)	(0.3859)	(0.2869)	(0.3847)	(0.5003)	(0.6628)	(0.0349)	(0.0623)	(0.0807)	(0.1045)	(37.9935)	(13.3297)
Bank size (log Assets)	0.0006	0.0021*	0.0040**	0.0066**	0.0006	0.0033*	0.0045**	0.0068***	0.0001	0.0005*	0.0007**	0.0011***	0.2811**	0.1515*
	(0.0005)	(0.0011)	(0.0016)	(0.0028)	(0.0008)	(0.0018)	(0.0019)	(0.0025)	(0.0001)	(0.0003)	(0.0003)	(0.0004)	(0.1100)	(0.0919)
Loan to assets ratio	0.0012	0.0047	0.0035	0.0011	0.0013	0.0011	0.0017	0.0026	0.0002	0.0003	0.0003	0.0003	0.8392*	0.3044
	(0.0023)	(0.0059)	(0.0061)	(0.0068)	(0.0023)	(0.0049)	(0.0046)	(0.0064)	(0.0004)	(0.0008)	(0.0007)	(0.0009)	(0.4537)	(0.3867)
Retail funding ratio	0.0004	0.0009	0.0048	0.0045	0.0023*	0.0025	0.0028	0.0047	0.0004*	0.0005	0.0007*	0.0010*	-0.1395	0.0304
	(0.0006)	(0.0023)	(0.0032)	(0.0036)	(0.0014)	(0.0019)	(0.0020)	(0.0029)	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.1416)	(0.1832)
Provision to assets ratio	-0.0177	-0.0247	-0.0251	-0.0049	-0.0018	-0.0198	-0.0086	0.0150	-0.0004	-0.0029	-0.0010	0.0028	-2.3126	-0.5301
	(0.0116)	(0.0235)	(0.0264)	(0.0260)	(0.0143)	(0.0225)	(0.0266)	(0.0335)	(0.0025)	(0.0040)	(0.0045)	(0.0054)	(2.5501)	(1.4323)
Capital adequacy ratio	0.0001	0.0006	0.0009*	0.0011	0.0003	0.0005	0.0006	0.0010	0.0001	0.0001	0.0001	0.0002	0.0023	0.0388
	(0.0002)	(0.0004)	(0.0006)	(0.0012)	(0.0002)	(0.0010)	(0.0010)	(0.0011)	(0.0000)	(0.0002)	(0.0002)	(0.0002)	(0.0682)	(0.0660)
Average risk weight	0.0005	0.0030	0.0030	0.0034	-0.0008	0.0047**	0.0037	0.0022	-0.0001	0.0008**	0.0006*	0.0004	-0.2609	-0.1766
	(0.0015)	(0.0022)	(0.0031)	(0.0047)	(0.0017)	(0.0022)	(0.0023)	(0.0037)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.2317)	(0.1765)
Economic activity	0.0076	0.0123	-0.0087	-0.0189	-0.0314	-0.0653**	-0.0680**	-0.0596	-0.0050	-0.0106**	-0.0108**	-0.0089	-1.8133	0.6914
	(0.0070)	(0.0254)	(0.0196)	(0.0216)	(0.0202)	(0.0305)	(0.0314)	(0.0405)	(0.0031)	(0.0050)	(0.0052)	(0.0065)	(1.7154)	(0.9594)
Lagged economic activity	-0.0002	0.0131	0.0197	0.0275	-0.0011	0.0082	0.0200	0.0329	0.0010	0.0026	0.0042*	0.0060*	0.8260	-0.2305
	(0.0049)	(0.0194)	(0.0213)	(0.0292)	(0.0095)	(0.0126)	(0.0144)	(0.0205)	(0.0017)	(0.0025)	(0.0026)	(0.0033)	(1.1667)	(0.8432)
Inflation	-0.0464	-0.0490	-0.0656	-0.0985**	-0.1641***	-0.1912***	-0.1593***	-0.1435***	-0.0265***	-0.0328***	-0.0274***	-0.0241***	-11.4599**	-9.2626**
	(0.0379)	(0.0405)	(0.0404)	(0.0404)	(0.0567)	(0.0623)	(0.0424)	(0.0504)	(0.0092)	(0.0108)	(0.0074)	(0.0084)	(4.5052)	(3.8375)
Obs.	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(1) p-value	0.0302	0.0175	0.0215	0.0521	0.0507	0.0613	0.0473	0.0508	0.0569	0.0674	0.0543	0.0544	0.0008	0.0144
AR(2) p-value	0.416	0.999	0.989	0.398	0.898	0.595	0.927	0.888	0.977	0.686	0.954	0.831	0.534	0.538
Hansen J p-value	0.647	0.423	0.748	0.492	0.605	0.535	0.652	0.61	0.568	0.65	0.752	0.683	0.615	0.752

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the systemic risk measures and the second lag of the competition measure. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B6: Systemic risk and competition: static panel results using bank level Lerner index with monthly data

Variables	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lerner	-0.2454***	-0.4567***	-0.4946***	-0.5788***	-0.0048***	-0.0063***	-0.0069***	-0.0076***	-0.0008***	-0.0010***	-0.0011***	-0.0012***	-0.3909***	-0.9444***
	(0.0924)	(0.1215)	(0.1217)	(0.1343)	(0.0009)	(0.0013)	(0.0014)	(0.0015)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.1294)	(0.1717)
Bank size (log Assets)	-0.1575***	-0.2277***	-0.2208***	-0.2020***	0.0014**	0.0010	0.0013*	0.0016**	0.0004***	0.0004***	0.0004***	0.0005***	-0.0400	0.0474
	(0.0335)	(0.0629)	(0.0639)	(0.0637)	(0.0006)	(0.0008)	(0.0008)	(0.0008)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0440)	(0.0672)
Loan to assets ratio	0.3102**	0.7838***	0.7995***	0.8626***	0.0015	0.0054	0.0065	0.0075*	0.0000	0.0005	0.0006	0.0008	0.5341***	0.0613
	(0.1508)	(0.2426)	(0.2495)	(0.2525)	(0.0027)	(0.0040)	(0.0041)	(0.0043)	(0.0004)	(0.0007)	(0.0007)	(0.0007)	(0.1762)	(0.2559)
Retail funding ratio	0.0336	-0.1651*	-0.1783**	-0.1933**	-0.0032***	-0.0055***	-0.0062***	-0.0069***	-0.0006***	-0.0010***	-0.0011***	-0.0012***	-0.0659	0.1698
	(0.0555)	(0.0864)	(0.0868)	(0.0842)	(0.0009)	(0.0012)	(0.0011)	(0.0012)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0727)	(0.1497)
Provision to assets ratio	3.8685**	5.9316**	5.7650**	5.4385**	0.0123	0.0089	0.0064	0.0037	0.0013	0.0006	0.0002	-0.0003	2.4801	-6.9046***
	(1.7096)	(2.3958)	(2.4659)	(2.6649)	(0.0170)	(0.0220)	(0.0233)	(0.0249)	(0.0027)	(0.0035)	(0.0037)	(0.0040)	(1.7912)	(1.7706)
Capital adequacy ratio	-0.0002	-0.0009**	-0.0009**	-0.0009*	0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0048***
	(0.0003)	(0.0005)	(0.0005)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0015)
Average risk weight	-0.3475***	-0.7200***	-0.7016***	-0.6952***	0.0000	-0.0034	-0.0039	-0.0044	0.0002	-0.0002	-0.0002	-0.0003	-0.2775*	-0.3571***
	(0.1215)	(0.2033)	(0.2090)	(0.2093)	(0.0027)	(0.0039)	(0.0040)	(0.0042)	(0.0004)	(0.0006)	(0.0007)	(0.0007)	(0.1461)	(0.1343)
Economic activity	0.0031	0.0191	0.0175	0.0165	-0.0002	-0.0003	-0.0003	-0.0003	-0.0000	-0.0000	-0.0000	-0.0000	-0.0067	-0.0091
	(0.0081)	(0.0157)	(0.0160)	(0.0171)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0130)	(0.0122)
Lagged economic activity	0.0013	-0.0059	-0.0054	-0.0084	0.0001	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	-0.0024	0.0136*
	(0.0069)	(0.0154)	(0.0156)	(0.0174)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0111)	(0.0076)
Inflation	-0.0251	-0.0436	-0.0416	-0.0386	-0.0004	-0.0008*	-0.0005	-0.0003	-0.0001*	-0.0001**	-0.0001	-0.0000	-0.0488*	-0.0368
	(0.0168)	(0.0338)	(0.0358)	(0.0410)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0270)	(0.0245)
Obs.	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420	4,420
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0	0	0	0	0	0	0	6.21e-11	0
Hansen J p-value	0.939	0.839	0.754	0.616	0.658	0.524	0.540	0.548	0.616	0.521	0.564	0.600	0.270	0.217
Weak-Instr. Kleibergen-Paap F	3644	3644	3644	3644	3644	3644	3644	3644	3644	3644	3644	3644	3644	3644

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). The model does not include a lagged dependent variable. Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM where we use as instruments the first four lags of the competition variable. The estimations were done in STATA using "xtivreg2" command. We have an unbalanced panel with monthly data for 46 banks from 2008M1 to 2019M3 (135 months). The F-test is used to test whether all variable coefficients are jointly zero. Weak-Instrument Kleibergen-Paap F detects if the instruments are weak. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Driscoll & Kraay standard errors reported in parentheses are robust to any pattern of heteroskedasticity and autocorrelation.

Table B7: Systemic risk and competition: baseline results using bank level Lerner index and minimum CAR of 10.5%

Variables	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lag 1 dep. var.	0.4594***	0.1703*	0.2067*	0.0480	0.6059**	0.0859	0.1200	0.0836	0.5725**	0.0796	0.1140	0.0761	0.5333***	0.5331***
	(0.1477)	(0.0873)	(0.1241)	(0.1086)	(0.2942)	(0.1011)	(0.1289)	(0.1469)	(0.2580)	(0.0804)	(0.1096)	(0.1313)	(0.1740)	(0.1236)
Lag 2 dep. var.	-0.0274	-0.2259*	-0.1965	-0.1272***	-0.0587	-0.0913***	-0.0605	0.0053	-0.0839	-0.0981***	-0.0803**	-0.0058	0.0666	0.1049***
	(0.0472)	(0.1253)	(0.1398)	(0.0334)	(0.1097)	(0.0342)	(0.0499)	(0.0699)	(0.0794)	(0.0320)	(0.0409)	(0.0593)	(0.0756)	(0.0213)
Lerner	-0.0564	-0.1316	-0.1291	-0.2093**	-0.0332	-0.0821**	-0.1049**	-0.1309**	-0.0081*	-0.0135***	-0.0175**	-0.0205**	-2.3445	-3.2247**
	(0.0401)	(0.0838)	(0.0854)	(0.0861)	(0.0231)	(0.0321)	(0.0432)	(0.0595)	(0.0049)	(0.0048)	(0.0069)	(0.0094)	(2.1455)	(1.4412)
Bank size (log Assets)	0.0092	0.0184	0.0202	0.0247*	0.0054	0.0117**	0.0164**	0.0205**	0.0013*	0.0019***	0.0027**	0.0032**	0.3049	0.6607***
	(0.0064)	(0.0112)	(0.0144)	(0.0131)	(0.0035)	(0.0049)	(0.0070)	(0.0088)	(0.0007)	(0.0007)	(0.0011)	(0.0013)	(0.2943)	(0.2223)
Loan to assets ratio	-0.0040	-0.0125	-0.0103	0.0113	-0.0033	-0.0041	-0.0087	-0.0104	-0.0006	-0.0005	-0.0013	-0.0017	0.7887	-0.6672
	(0.0086)	(0.0159)	(0.0270)	(0.0297)	(0.0043)	(0.0071)	(0.0104)	(0.0154)	(0.0006)	(0.0012)	(0.0016)	(0.0024)	(0.9040)	(0.5933)
Retail funding ratio	-0.0001	0.0135	0.0051	-0.0288**	0.0012	-0.0032	-0.0038	-0.0059	0.0005	-0.0005	-0.0004	-0.0008	0.2511	-0.0731
	(0.0062)	(0.0140)	(0.0144)	(0.0142)	(0.0029)	(0.0052)	(0.0069)	(0.0076)	(0.0006)	(0.0008)	(0.0011)	(0.0012)	(0.3754)	(0.4646)
Provision to assets ratio	-0.0035	0.0394	0.0892	0.0124	-0.0161	0.0016	0.0207	0.0787	-0.0036	-0.0004	0.0028	0.0132	-0.1318	-5.8067
	(0.0459)	(0.0884)	(0.1186)	(0.1384)	(0.0239)	(0.0443)	(0.0554)	(0.1156)	(0.0042)	(0.0068)	(0.0084)	(0.0184)	(5.1665)	(3.8579)
Capital adequacy ratio	0.0021	0.0029	0.0023	0.0057	0.0012	0.0018	0.0014	0.0001	0.0002	0.0003	0.0002	0.0000	0.1353	0.0456
	(0.0033)	(0.0063)	(0.0061)	(0.0080)	(0.0017)	(0.0027)	(0.0034)	(0.0046)	(0.0003)	(0.0004)	(0.0005)	(0.0007)	(0.3556)	(0.1981)
Average risk weight	0.0108**	0.0208	0.0185	0.0202*	0.0066***	0.0094*	0.0120	0.0081	0.0011***	0.0015	0.0020*	0.0013	-0.5495	0.0688
	(0.0051)	(0.0133)	(0.0152)	(0.0116)	(0.0023)	(0.0054)	(0.0074)	(0.0076)	(0.0003)	(0.0009)	(0.0012)	(0.0012)	(0.4992)	(0.3088)
Economic activity	-0.1017***	-0.3180***	-0.2937**	-0.2629**	-0.0584**	-0.1211***	-0.1270***	-0.1070***	-0.0107***	-0.0187***	-0.0199***	-0.0162**	-0.9831	-3.4069
	(0.0293)	(0.1148)	(0.1309)	(0.1090)	(0.0276)	(0.0303)	(0.0300)	(0.0413)	(0.0034)	(0.0043)	(0.0048)	(0.0066)	(2.5376)	(2.1667)
Lagged economic activity	-0.0804***	-0.0073	-0.0448	0.0820	-0.0346	0.0085	0.0014	0.0016	-0.0033	0.0032	0.0021	0.0020	-1.2260	-2.4475*
	(0.0304)	(0.0718)	(0.0983)	(0.1108)	(0.0248)	(0.0297)	(0.0444)	(0.0538)	(0.0038)	(0.0042)	(0.0059)	(0.0077)	(1.9420)	(1.4575)
Inflation	-0.2152	-0.0594	-0.1133	0.0492	-0.1585**	-0.1807	-0.2531*	-0.2555	-0.0344**	-0.0303*	-0.0408**	-0.0380	-26.1180**	-27.4728***
	(0.1349)	(0.1944)	(0.1516)	(0.3151)	(0.0755)	(0.1290)	(0.1452)	(0.1726)	(0.0153)	(0.0169)	(0.0205)	(0.0244)	(10.1491)	(7.2906)
Obs.	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(1) p-value	0.207	0.0383	0.0393	0.0222	0.143	0.0957	0.0595	0.0285	0.0822	0.0766	0.0489	0.0248	0.00116	0.0361
AR(2) p-value	0.308	0.965	0.828	0.850	0.808	0.664	0.789	0.996	0.821	0.678	0.825	0.961	0.932	0.675
Hansen J p-value	0.517	0.0452	0.0208	0.334	0.431	0.464	0.393	0.347	0.585	0.507	0.425	0.325	0.313	0.696

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B8: Systemic risk and competition: baseline results using bank level Lerner index and excluding investment banks from the sample

Variables	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Lagged dep. var.	0.6556***	0.2370***	0.3829***	0.3076***	0.9761**	0.2125	0.0761	-0.0879	1.0231***	0.3175*	0.1574	-0.0663	0.1515*	0.6144***
	(0.0683)	(0.0673)	(0.0702)	(0.0574)	(0.4180)	(0.1572)	(0.1150)	(0.0881)	(0.3455)	(0.1667)	(0.1295)	(0.0862)	(0.0853)	(0.0586)
Lerner	-0.0189*	-0.0517*	-0.0670*	-0.1194*	-0.0145	-0.1029**	-0.1114***	-0.1730***	-0.0031	-0.0155**	-0.0173***	-0.0267***	-4.1688**	-1.2924**
	(0.0110)	(0.0274)	(0.0343)	(0.0611)	(0.0180)	(0.0453)	(0.0397)	(0.0572)	(0.0030)	(0.0075)	(0.0063)	(0.0095)	(1.7279)	(0.6510)
Bank size (log Assets)	0.0026	0.0080*	0.0115**	0.0222**	0.0018	0.0161**	0.0172***	0.0267***	0.0004	0.0024**	0.0027***	0.0042***	0.7743***	0.4733***
	(0.0019)	(0.0043)	(0.0055)	(0.0095)	(0.0035)	(0.0070)	(0.0065)	(0.0092)	(0.0006)	(0.0011)	(0.0010)	(0.0015)	(0.2835)	(0.1828)
Loan to assets ratio	-0.0004	0.0070	-0.0021	-0.0091	-0.0023	-0.0029	0.0009	0.0044	0.0001	-0.0007	-0.0002	0.0003	1.5369*	0.4941
	(0.0047)	(0.0107)	(0.0109)	(0.0136)	(0.0070)	(0.0095)	(0.0090)	(0.0129)	(0.0010)	(0.0015)	(0.0014)	(0.0020)	(0.8294)	(0.4160)
Retail funding ratio	0.0002	0.0023	0.0073	0.0097	0.0027	0.0044*	0.0048**	0.0079*	0.0006	0.0010**	0.0011**	0.0014**	-0.0269	-0.0241
	(0.0009)	(0.0031)	(0.0048)	(0.0068)	(0.0026)	(0.0026)	(0.0024)	(0.0041)	(0.0004)	(0.0005)	(0.0004)	(0.0007)	(0.2133)	(0.1727)
Provision to assets ratio	-0.0286*	-0.0613	-0.0647	-0.0495	-0.0083	-0.0342	-0.0249	-0.0229	-0.0008	-0.0056	-0.0040	-0.0029	-2.9641	-1.1822
	(0.0172)	(0.0385)	(0.0402)	(0.0480)	(0.0278)	(0.0398)	(0.0384)	(0.0492)	(0.0043)	(0.0062)	(0.0059)	(0.0077)	(3.1973)	(1.8542)
Capital adequacy ratio	-0.0002	0.0009	0.0011	0.0018	0.0003	0.0015	0.0017	0.0016	0.0001	0.0003	0.0003	0.0003	0.0021	-0.0547*
	(0.0007)	(0.0019)	(0.0024)	(0.0029)	(0.0010)	(0.0025)	(0.0027)	(0.0032)	(0.0001)	(0.0004)	(0.0004)	(0.0005)	(0.1260)	(0.0331)
Average risk weight	0.0013	0.0022	0.0048	0.0107	0.0021	0.0047	0.0009	-0.0020	-0.0000	0.0011	0.0005	0.0001	-0.8049**	-0.1563
	(0.0037)	(0.0073)	(0.0078)	(0.0088)	(0.0047)	(0.0068)	(0.0058)	(0.0065)	(0.0008)	(0.0011)	(0.0010)	(0.0010)	(0.3996)	(0.2610)
Economic activity	0.0129	0.0415*	0.0084	0.0126	-0.0160	-0.0630*	-0.0695**	-0.0671**	-0.0028	-0.0094*	-0.0103**	-0.0085	-2.2172	2.4068***
	(0.0100)	(0.0250)	(0.0189)	(0.0309)	(0.0192)	(0.0345)	(0.0278)	(0.0327)	(0.0029)	(0.0056)	(0.0045)	(0.0053)	(1.7251)	(0.8795)
Lagged economic activity	0.0008	0.0260	0.0214	0.0590	-0.0110	0.0301	0.0429**	0.0728***	-0.0001	0.0050	0.0071**	0.0118***	1.8630**	-0.0360
	(0.0065)	(0.0213)	(0.0217)	(0.0394)	(0.0146)	(0.0219)	(0.0179)	(0.0220)	(0.0025)	(0.0037)	(0.0030)	(0.0038)	(0.9355)	(0.6069)
Inflation	-0.0719*	-0.0610	-0.0906*	-0.1362***	-0.1374**	-0.2265***	-0.1879***	-0.2179***	-0.0279***	-0.0402***	-0.0337***	-0.0363***	-14.6651***	-9.5446**
	(0.0429)	(0.0510)	(0.0476)	(0.0490)	(0.0548)	(0.0719)	(0.0517)	(0.0523)	(0.0100)	(0.0120)	(0.0084)	(0.0088)	(4.3559)	(4.4220)
Obs.	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,250
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	6.00e-11	8.17e-09	0	0	0	0	0	0	0
AR(1) p-value	0.0201	0.0372	0.0162	0.0400	0.130	0.0606	0.134	0.240	0.116	0.0393	0.0842	0.213	0.00258	0.0347
AR(2) p-value	0.300	0.907	0.939	0.734	0.990	0.992	0.593	0.230	0.850	0.839	0.802	0.215	0.889	0.478
Hansen J p-value	0.693	0.880	0.899	0.249	0.390	0.587	0.786	0.304	0.743	0.480	0.563	0.213	0.893	0.741

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the two step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks and we use the Windmeijer (2005) finite sample correction.

Table B9: Systemic risk and competition: baseline results using bank level Lerner index and one step GMM estimator

	Failed bank assets to sum of total assets				Interbank loss to regulatory capital				Interbank loss to RWAs				NBF	SBF
Variables	(1) Avg.	(2) VaR (95%)	(3) E.S. (95%)	(4) Max	(5) Avg.	(6) VaR (95%)	(7) E.S. (95%)	(8) Max	(9) Avg.	(10) VaR (95%)	(11) E.S. (95%)	(12) Max	(13) Avg.	(14) Avg.
Variables	Avg.	Q95	E.S. 95	Max	Avg.	Q95	E.S. 95	Max	Avg.	Q95	E.S. 95	Max	Avg.	Avg.
Lagged dep. var.	0.6378***	0.2729***	0.4118***	0.2913***	0.9598***	0.1357	0.0528	-0.0503	0.9513***	0.1835	0.0929	-0.0382	0.1670*	0.6712***
	(0.0667)	(0.1010)	(0.0779)	(0.0564)	(0.2978)	(0.1662)	(0.1462)	(0.1442)	(0.3054)	(0.1750)	(0.1424)	(0.1377)	(0.0879)	(0.1273)
Lerner	-0.0136*	-0.0381**	-0.0473**	-0.0805**	-0.0275	-0.0762***	-0.0774***	-0.1032***	-0.0040	-0.0117***	-0.0118***	-0.0158***	-3.1071**	-0.9035*
	(0.0080)	(0.0185)	(0.0227)	(0.0367)	(0.0186)	(0.0285)	(0.0277)	(0.0372)	(0.0030)	(0.0044)	(0.0042)	(0.0057)	(1.2224)	(0.5402)
Bank size (log Assets)	0.0017	0.0048*	0.0067**	0.0120**	0.0035	0.0094**	0.0101**	0.0143***	0.0005	0.0015**	0.0016**	0.0022***	0.5261***	0.3036**
	(0.0011)	(0.0025)	(0.0033)	(0.0055)	(0.0028)	(0.0041)	(0.0041)	(0.0054)	(0.0004)	(0.0006)	(0.0006)	(0.0008)	(0.1728)	(0.1535)
Loan to assets ratio	0.0012	0.0038	-0.0012	-0.0065	-0.0012	-0.0025	-0.0014	-0.0025	-0.0001	-0.0005	-0.0003	-0.0005	0.9550*	0.5447
	(0.0032)	(0.0070)	(0.0074)	(0.0089)	(0.0038)	(0.0064)	(0.0062)	(0.0086)	(0.0006)	(0.0010)	(0.0010)	(0.0013)	(0.5566)	(0.3921)
Retail funding ratio	0.0007	0.0017	0.0067	0.0093	0.0034	0.0018	0.0031	0.0063*	0.0006*	0.0004	0.0007	0.0012**	-0.0536	-0.0906
	(0.0011)	(0.0030)	(0.0045)	(0.0063)	(0.0020)	(0.0026)	(0.0026)	(0.0035)	(0.0003)	(0.0005)	(0.0004)	(0.0006)	(0.2080)	(0.2016)
Provision to assets ratio	-0.0309**	-0.0494	-0.0529	-0.0259	-0.0096	-0.0320	-0.0164	0.0078	-0.0013	-0.0049	-0.0021	0.0019	-2.1076	-0.8461
	(0.0157)	(0.0357)	(0.0403)	(0.0418)	(0.0242)	(0.0338)	(0.0324)	(0.0391)	(0.0041)	(0.0054)	(0.0053)	(0.0062)	(3.0870)	(1.7412)
Capital adequacy ratio	0.0004	0.0010	0.0010	0.0001	0.0007	0.0010	0.0013	0.0012	0.0001	0.0002	0.0002	0.0002	0.0520	-0.0077
	(0.0006)	(0.0015)	(0.0019)	(0.0024)	(0.0009)	(0.0020)	(0.0021)	(0.0028)	(0.0001)	(0.0003)	(0.0003)	(0.0004)	(0.1272)	(0.0738)
Average risk weight	0.0003	0.0029	0.0031	0.0014	0.0005	0.0033	0.0016	0.0001	0.0000	0.0006	0.0003	0.0001	-0.4662**	-0.2954
	(0.0021)	(0.0035)	(0.0044)	(0.0050)	(0.0020)	(0.0036)	(0.0033)	(0.0044)	(0.0003)	(0.0006)	(0.0005)	(0.0007)	(0.2326)	(0.2120)
Economic activity	0.0081	0.0261	-0.0007	-0.0179	-0.0279	-0.0616**	-0.0663**	-0.0578*	-0.0041	-0.0094**	-0.0100**	-0.0082	-1.7871	0.5287
	(0.0083)	(0.0277)	(0.0215)	(0.0265)	(0.0203)	(0.0271)	(0.0273)	(0.0329)	(0.0032)	(0.0043)	(0.0044)	(0.0053)	(1.4890)	(1.1669)
Lagged economic activity	-0.0006	0.0219	0.0209	0.0359	-0.0023	0.0230	0.0320	0.0450*	0.0009	0.0042	0.0056*	0.0077*	1.3534	-0.3909
	(0.0053)	(0.0224)	(0.0235)	(0.0355)	(0.0142)	(0.0182)	(0.0202)	(0.0274)	(0.0026)	(0.0030)	(0.0032)	(0.0043)	(1.0818)	(0.8425)
Inflation	-0.0516	-0.0661	-0.0857**	-0.1144***	-0.1817***	-0.1806***	-0.1574***	-0.1615***	-0.0292***	-0.0305***	-0.0268***	-0.0261***	-11.7458***	-10.1967**
	(0.0371)	(0.0443)	(0.0425)	(0.0427)	(0.0655)	(0.0681)	(0.0519)	(0.0557)	(0.0104)	(0.0115)	(0.0085)	(0.0090)	(4.3539)	(4.0823)
Obs.	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501	1,501
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test p-value	0	0	0	0	0	0.00146	2.22e-09	0	0	9.73e-05	0	0	0	0
AR(1) p-value	0.0316	0.0181	0.0177	0.0273	0.0555	0.117	0.0572	0.0277	0.0527	0.0935	0.0442	0.0240	0.00177	0.00345
AR(2) p-value	0.296	0.848	0.978	0.579	0.929	0.784	0.451	0.556	0.847	0.921	0.521	0.539	0.986	0.608
Hansen J p-value	0.0390	0.526	0.985	0.858	0.290	0.169	0.866	0.891	0.425	0.178	0.916	0.898	0.572	0.645

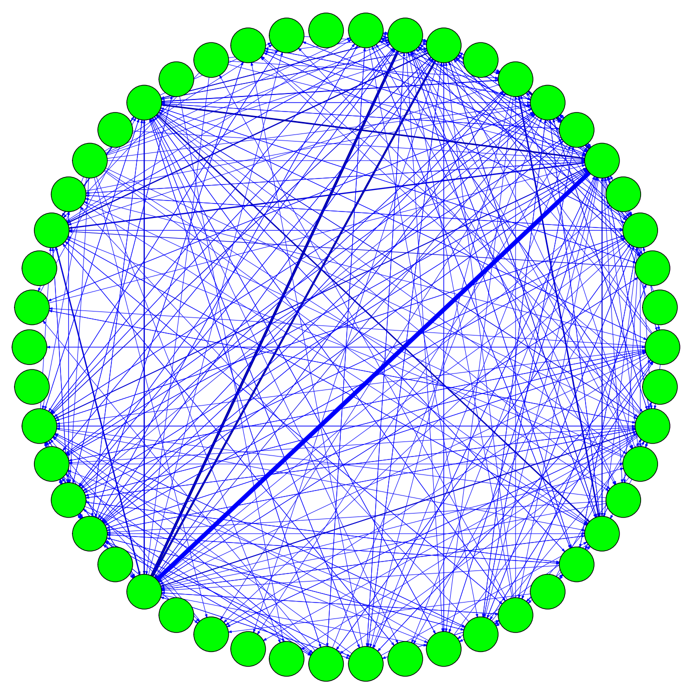
Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). Regression results of eq.(2), $SR_{i,t} = \alpha_i + \lambda_t + \rho SR_{i,t-1} + \beta C_{i,t} + \zeta Z_t + \delta X_{i,t-2} + \epsilon_{i,t}$, where each column refers to one systemic risk measure ($SR_{i,t}$). Variable definitions are described in section 3.3 and table A1 in Appendix A. Standard errors are reported in parenthesis below their coefficient estimates. The estimation was done using the one step GMM Arellano-Bond estimator where we use as instruments the second and third lag of the competition and systemic risk measures. The estimations were done in STATA using "xtabond2" command. We curtail the instruments and collapse them to have unique moment conditions. We have an unbalanced panel with quarterly data for 46 banks from 2008Q1 to 2019Q1 (i.e. 45 quarters). The F-test is used to test whether all variable coefficients are jointly zero. The AR(1) and AR(2) p-values are used to test the first and second order serial correlation in the residuals. The Hansen J test is distributed under the null hypothesis asymptotically as a χ^2 with $m - k$ degrees of freedom, where m is the number of instruments and k is the number of endogenous variables. Standard errors are robust to any pattern of heteroskedasticity and correlation within banks.

Appendix C

In this section, we illustrate the structure of the Mexican interbank exposure network and we provide more details on how the sequential default algorithm works. Figure C1 shows an example of the structure of the interbank exposure network on the last day of month. The circles denote bank institutions and its size is the same to preserve bank anonymity. The solid blue lines denote the links between any bank i and any bank j. There are parts of the chart that are more dense than others because some institutions are more interconnected. The structure of the network is time-varying and it changes for each period t.

Figure C1: Structure of the interbank exposure network on any day t



Source: Banco de México.
Notes: This Figure illustrates the structure of the Mexican interbank exposure network over any day. The dots or circles represent bank institutions, whereas each blue line is the bilateral aggregated link between any bank i and any bank j. The dot size is the same to ensure bank anonymity. Moreover, we do not specify the exact date because of the confidential nature of our data.

The sequential default algorithm can be summarized in a five-step process as follows:

1. We select a bank b from the set of banks B and assume that it fails. This generates the initial shock, which we denote as S.

2. The initial shock S is transmitted through the bank's network and it affects other banks through interbank exposures. We denote s^b as the set of banks affected by the initial shock generated by bank b.

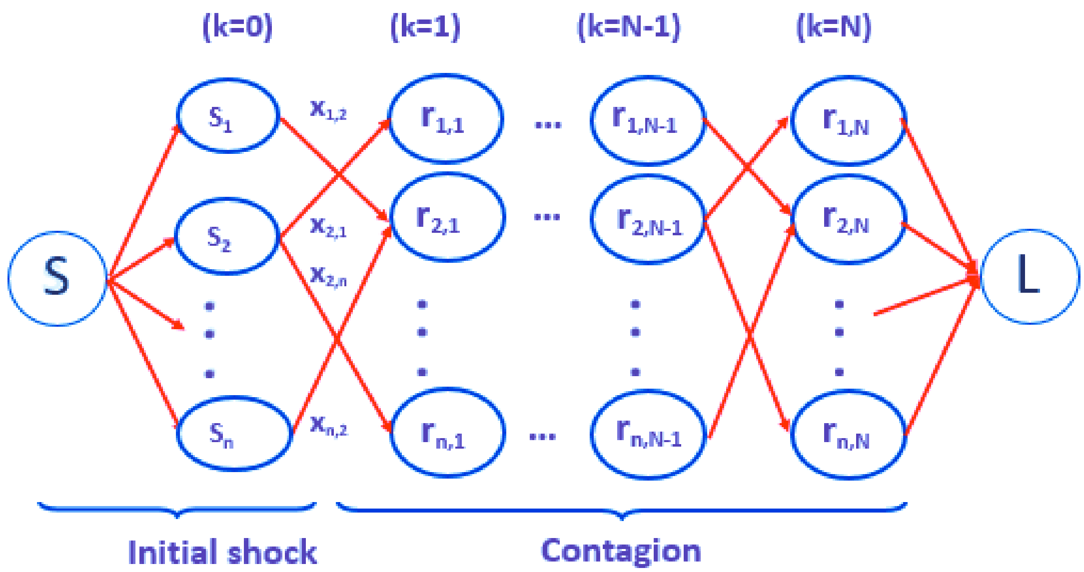
3. If the initial shock S is sufficiently large to reduce any bank's CAR lower than 8 percent in s^b affected by the initial shock, then an additional round of contagion is triggered. During any additional round, banks may fail as an indirect consequence of the initial shock S (i.e., second order effects). We denote as $s_{b,n}$ the set of banks that are affected (and may fail) in the n contagion round as a consequence of the initial shock (S) triggered by the idiosyncratic failure of bank b. Obviously $s_{b,1} = s^b$.

4. The contagion rounds stop once there is no additional bank failure. We sum all bank losses (i.e., over all the contagion rounds) to compute the banking sector loss as a result of an idiosyncratic bank initial shock. Moreover, we compute the share of affected banking sector assets.

5. This process is repeated for all banks available in B.

Figure C2 shows a diagram that describes how the sequential default algorithm evolves.

Figure C2: Sequential default model algorithm



Source: Banco de México.
Notes: This Figure shows the sequential default algorithm. Each bank s_i is exposed to an initial shock S, x_{ij} is the size of the aggregate interbank exposure between bank i and bank j, r_{ij} is the j bank affected in each contagion round k as a result of the failure of bank i, whereas L is the aggregate sum of interbank loss as a result of the contagion chain attributable to the initial shock S.

Appendix D

To estimate the Boone indicator we follow Schaeck and Cihák (2014) and this is fully described in Bátiz-Zuk and Lara-Sánchez (2022). This indicator is the β_t coefficient for each period t of the following profitability equation:

$$\pi_{it} = \alpha_i + \gamma_t + \beta_t log(\hat{C}_{it}) + \delta X_{it} + \epsilon_{it}, \tag{d1}$$

where π_{it} is the ratio of profit to total assets of bank i at time t, α_i and γ_t are bank and time fixed effects to consider unobserved heterogeneity, $\hat{C}_{it}$ is the ratio of bank's cost to revenue, and X_{it} are bank specific control variables. We use as control variables the following four bank specific ratios: provision to total assets, loans to non-financial private firms and households to total assets, retail funding to total liabilities and average risk weights. To estimate the Boone indicator we rely on a rolling window of 6 quarters. In this paper, to estimate eq.(d1) we use a two-step generalized method of moments (GMM) estimator with clustered standard errors at the bank level. This approach deals with endogeneity concerns as described by Bátiz-Zuk and Lara-Sánchez (2022).[52,53]

The underlying principle of the Boone indicator is based on the idea that efficient banks achieve superior performance in terms of higher profits compared with inefficient banks. Moreover, in an intense competitive environment, this process may serve efficient banks to attain a higher market share. In other words, this implies that in a competitive market, profits of inefficient banks will be adversely affected compared with efficient banks.

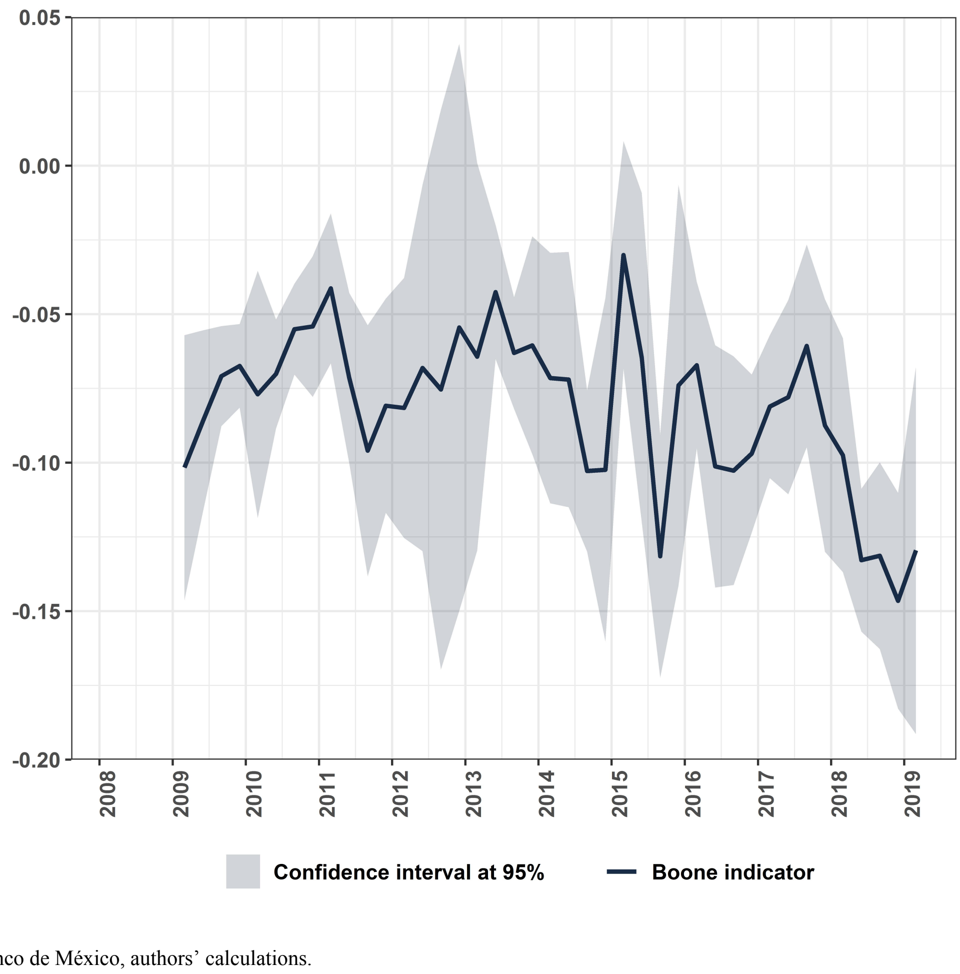
Figure D1 shows the estimates for the Boone indicator as well as the 95 percent confidence interval. As in other empirical papers (see de Ramon and Straughan (2020)), our Boone indicator is negative for the sample period and it is significantly less smooth than any of the other competition measures analyzed in this study. There is no definite trend for the sample period but if we compare the starting with the end of sample period, this indicator suggests that there is more intense competition. The values of this indicator decrease significantly after 2013.

[52] Endogeneity concerns may arise because the most efficient banks may have the highest market power.

[53] In theory, the Boone indicator is expected to be negative because any increase in bank's cost should decrease its profit. In this regard, a more efficient bank will have a β (i.e., Bone indicator) closer to zero. However, in practice, the Boone indicator may be positive when firms compete in quality (see Tabak et al. (2012))

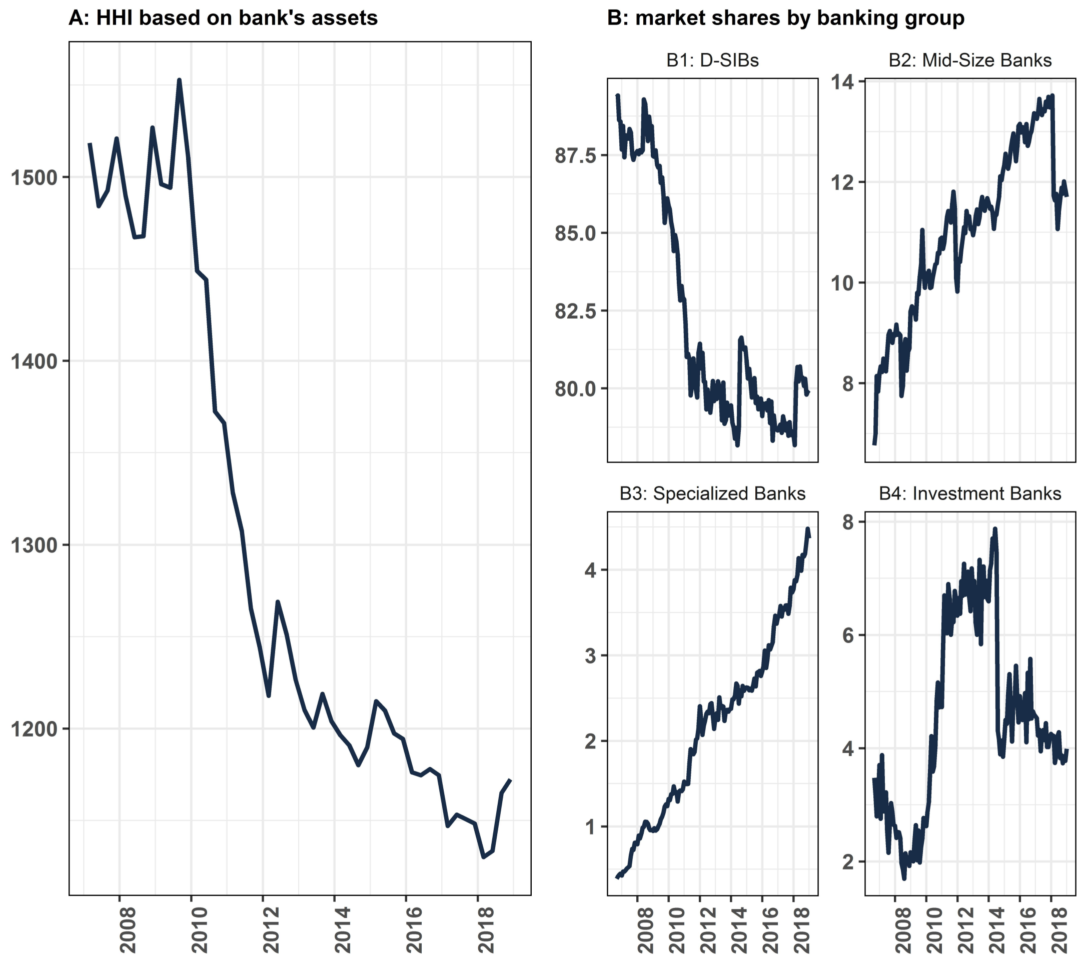
Figure D2 Panel A shows the HHI concentration index for total assets. This Figure suggests that concentration decreased over the sample period. This is because both medium and small size banks increased their market share. Before the financial crisis, our data shows that total assets were concentrated in a few large banks. Since there is no spike in the evolution of the HHI, we can conclude that none of the bank mergers that occurred over this period can be considered as large or noteworthy. Panel B shows the evolution of the market shares, where we classified data by banking groups. We observe that D-SIBs have market shares beyond 75 percent, but there is an upward trend for Mid-Sized Banks, Specialized Banks and Investment Banks.

Figure D1: Evolution of the Boone indicator over time: 2008Q1-2019Q1



Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of the Boone indicator over the sample period 2008Q1 to 2019Q1. The shaded areas are the 95 percent confidence interval around our Boone estimate. An increase in the Boone indicator is associated to less intense competition. The labels on the horizontal axis indicate the beginning of the year.

Figure D2: Evolution of structural competition measures over time: 2008Q1-2019Q1



Source: Banco de México, authors' calculations.
Notes: This Figure shows the evolution of structural competition measures over the sample period 2008Q1 to 2019Q1. Panel A shows the HHI based on total assets. In turn, each Panel within Panel B shows bank market shares based on total assets grouped by bank type. Panel B1 shows D-SIBs market shares based on total assets. Panel B2 shows Mid-Sized banks market shares based on total assets. Panel B3 shows Specialized banks market share based on total assets. Panel B4 shows Investment banks market shares based on total assets. Data are available from January 2008 to March 2019.

Appendix E

In Mexico, CNBV classifies banks based on the level of their capital ratio into five categories.[54] No action is required when the following three requirements are met: (i) the bank's regulatory capital ratio is greater than 10.5 percent, (ii) the Tier 1 ratio is greater than 8.5 percent; and (iii) the Core Tier 1 ratio is greater than 7 percent. If the bank's capital ratio falls in the interval from 10.5 to 8 percent or if the Tier 1 ratio falls in the interval from 8.5 to 7 percent or if the Core Tier 1 ratio falls in the interval from 7 to 4.5 percent, then the bank must take prompt corrective actions.[55] If the bank's capital ratio falls in the range from 7 to 8 percent or if the Tier 1 ratio falls lower than 6 percent or if the Core Tier 1 ratio falls lower than 4 percent, then the bank must take additional and stricter actions.[56] If the bank's capital ratio falls in the range from 4 to 7 percent, then the bank's activity is severely limited, and the bank enters into the resolution process if the solvency ratio falls lower than 4 percent.[57]

[54] For specific details see https://www.gob.mx/cnbv/acciones-y-programas/alertas-tempranas-banca-multiple#:~:text=En%20M%C3%A9xico%20el%20ICAP%20m%C3%ADnimo%20es%20de%208.0%25%3B,deben%20cumplir%20con%20un%20nivel%20m%C3%ADnimo%20de%2010.5%25;accessedon8October2020.

[55] In particular, the bank must: (i) submit a detailed report of its financial situation along with a capital conservation plan; (ii) refrain from conducting operations that may lead to a reduction in its regulatory capital ratio lower than the minimum requirement of 8 percent; (iii) restrict partially the payment of dividends, compensations and any additional extraordinary bonus; and (iv) refrain from increasing funding granted to relevant related counterparties (i.e., groups of connected counterparties).

[56] In particular, the bank must: (i) present a plan to restore its capital; (ii) suspend dividend payments and share buybacks; (iii) defer the payment of interest and principal or convert in advance the outstanding subordinated obligations; (iv) suspend payment of any additional compensation and extraordinary bonus; and (v) refrain from agreeing to increase the loan size of outstanding loans granted to related persons.

[57] In particular, the bank will not be able to carry out new investments in non-financial assets and/or open branches and carry out new activities other than the operations that are done regularly.