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Measuring the evolution of competition and the impact of the financial reform in the Mexican banking sector, 2008-2019*

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Abstract: This paper analyzes the monthly evolution of bank competition in Mexico from 2008 to 2019 using different measures. Subsequently, we analyze whether the 2014 financial reform had an effect on some of our competition measures. We use ordinary and quantile regression techniques and Markov switching models to identify changes in regimes. We find partial empirical evidence supporting the idea that the reform had a positive average effect and increased banks competition intensity during a few years. However, we also document heterogeneity as some large banks benefited from an increase in their market power. We perform several robustness tests and report that our measures lead to values that are congruent and similar to those available in the literature. The main policy lesson of our research is that regulators could benefit from the monitoring of competition evolution using a finer time frequency.

Keywords: competition measures, regulatory impact, financial reforms, banks, bank mergers

JEL Classification: D40, G21, G28, L10, L11, L50

Resumen: Este trabajo analiza la evolución mensual de la competencia bancaria en México de 2008 a 2019 usando distintas medidas de competencia. Además, se analiza si la reforma financiera de 2014 tuvo efecto en algunas de estas métricas. Se utilizan técnicas de regresión estándar y cuantílica y modelos de Markov para identificar cambios en regímenes. Se encuentra evidencia empírica parcial que respalda la idea de que la reforma tuvo un efecto promedio positivo e incrementó la intensidad de la competencia de los bancos durante algunos años, si bien estos son heterogéneos debido a que algunos bancos grandes registraron incrementos en su poder de mercado. Se realizaron diversas pruebas de robustez y se reporta que las medidas analizadas conducen a valores que son congruentes y similares a los disponibles en la literatura. La principal recomendación de esta investigación es la relevancia de dar seguimiento de la evolución de la competencia utilizando una frecuencia de tiempo más alta.

Palabras Clave: medidas de competencia, impacto regulatorio, reformas financieras, bancos, fusiones bancarias

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1 Introduction

It is well known that competition in the banking sector¹ is unobservable, and this has led researchers to develop a number of measures. As of today, there is no generalized agreement on what is the best measure to assess competition in the banking industry. As shown by Liu et al. (2013), the choice of a specific measure may lead to a different result in terms of competition intensity. This study analyzes the evolution and performance of multiple measures of competition to assess if there is evidence of any regime change for the Mexican banking sector between 2008 and 2019. Two critical events took place during this period. First, the global financial crisis² during the period from 2008:Q4 to 2009:Q4, which can be regarded as an external exogenous shock that eventually changed the international regulatory framework. Second, the Mexican financial reform enacted in 2014 was an internal regulatory factor that aimed to primarily boost competition in the banking sector both in the short and long run. Mexico provides a useful case study, as competition in the Mexican banking sector is expected to intensify following the financial reform.

We compute a number of competition measures that provide alternative views on the evolution of competition. Specifically, we follow a classical approach and compute the number of banks, the concentration ratio, and the Herfindahl-Hirschman Index (*HHI*) to assess the structure of the Mexican banking sector. Next, we calculate and compare three competition measures: the Lerner index (Lerner (1934)) under a standard (Berger et al. (2009)) and a refined approach (Coccoresse (2014)) and the Boone indicator (Boone (2008)) for the Mexican Banks from 2008 to 2019. In addition, we construct a composite indicator using principal components based on the three competition indicators (i.e., standard and refined Lerner and Boone). Moreover, we analyze static and 36-month rolling window correlations among competition measures to identify common trends between them. We use traditional regression analysis and split our data in three subsamples (i.e., crisis 2008-2009, post-crisis 2010-2013, and post-reform 2014-2019) to assess the evolution of the distribution of the competition

¹According to Article 3 of the Mexican Credit Institutions Law (LIC, its acronym in Spanish), the Mexican banking system comprises the central bank, all commercial and development banks, and public trusts created by the Federal Government as well as by self-regulatory banking entities. In this paper, the banking sector refers exclusively to commercial banks.

²This crisis can be broadly characterized as a global liquidity shock that drained the availability of funds in debt markets. In Mexico, there was a capital flow reversal, and this affected banks as well as many non-bank financial intermediaries (NBFIs). Banks faced difficulties and had to cut their lending. However, non-bank financial corporations of limited purpose (i.e., SOFOLES, the acronym in Spanish) suffered significantly more as banks cut their lending to them (see Berrospide and Herreras (2015)).

measures. We also use linear regression at the sector and bank level to identify if there is, on average, more or less intensity in competition due, in part, to the 2014 financial reform. Then, we use quantile regression at the bank level to test if the reform exerts a heterogeneous effect across bank types. Finally, we use Markov switching models to identify if there is any endogenous change in regimes related to the reform implementation date. Interestingly, using different indicators allows us to report opposing or divergent outlook depending on the competition measure under analysis.

Empirical evidence on the evolution of competition in the Mexican banking sector is scarce. Studies that have analyzed the performance of competition in Mexico are limited in the sense that none of them has incorporated the period when the 2014 financial reform occurred. Further, none of the previous studies has analyzed all the measures taken into account in this paper. Montemayor (2003) tests the structure-conduct-performance paradigm and the efficient structure hypothesis for the post-1995 crisis period and concludes that both hypotheses contribute to the explanation of banks' profitability. Maudos and Solís (2011) use annual data for the period from 1993 to 2005 and compute the H -statistic and the Lerner index. They find evidence that supports the view that the banking sector is best characterized as monopolistic competition. This result is consistent with the previous findings of the following researchers: Negrín et al. (2010) for a sample of Mexican Banks from 2000 to 2007; Claessens and Laeven (2003) for a sample of international banks from 1994 to 2001; and Gelos and Roldos (2004) for a sample of emerging market banks from 1994 to 1999. Garza-García (2012) examines the evolution of bank efficiency for the Mexican banking sector from 2001 to 2009. He finds that efficiency increased from 2001 to 2006, while a sharp decrease took place from 2006 to 2008. Castellanos et al. (2013) analyze the efficiency of banks and its relationship with the intensity of competition from 2002 to 2012. Their main finding is that there are increasing trends of efficiency in the banking sector during their period of study, while local banks are more efficient than foreign-owned banks.³ Berrospide and Herrerias (2015) study the impact of the global financial crisis on SOFOLES from 2001 to 2011. They find evidence supporting the view that the liquidity shock explains 64 percent of the lending contraction of SOFOLES, while deregulatory policies had a minor and almost unnoticeable role.

To the best of our knowledge, there are no comprehensive studies in Mexico that have analyzed competition between banks over a sufficiently long period. There are empirical studies using multi-country samples, including Mexican Banks, which offer a partial and supplemen-

³See Castellanos et al. (2013) for a comprehensive study on bank competition and efficiency.

tary view to our analysis. In any case, cross-country studies have at least three limitations. First, due to the data selection processes, most of these studies typically have a limited sample coverage for some countries, especially those like Mexico where foreign banks have a large presence.⁴ This occurs even when they use banks' unconsolidated statements to include internationally active banks' domestic and foreign subsidiaries as separate entities. Second, these studies fail to assess the impact of specific or idiosyncratic events and business cycles that take place in any country. This limits the understanding of the evolution of the intensity of competition. Moreover, multi-country studies are more complex in that they have to control for heterogeneity among countries. Third, as highlighted by de Ramon and Straughan (2019, p.2), many multi-country studies analyze competition measures during different time periods, and this often led to mixed and, sometimes, matchless results.

Our paper contributes to the literature on competition in several ways. First, using a novel regulatory data-set, we develop monthly indicators to characterize the evolution of competition. For each indicator, we validate our results using quarterly data; moreover, we check the adequacy of our estimates in relation to empirical results reported in the literature for both advanced and emerging banking sectors. Second, we report significant differences between the standard Lerner approach and its refined version, which have strong implications for assessing the evolution of competition intensity. Third, we use regression analysis and explore if the financial reform increases or decreases bank competition on average. Fourth, we use quantile regression and test whether there is any sign of heterogeneous effect per bank type in the period following the 2014 financial reform. Fifth, we use a regime-switching technique to evaluate if there is any statistical change attributable to the implementation of the financial reform. Conditional on the identification of a regime switch in a date close enough to the reform implementation, this method also allows the estimation of a proxy for the duration of the reform effect.⁵ To the best of our knowledge, this is the only paper that analyzes average, heterogeneous, and duration effects stemming from a financial regulatory reform using multiple competition measures for almost all commercial banks in a single emerging-market country during a relatively long time period.

⁴For example, using the Bankscope data set, Coccorese, (2014, p.79) covers approximately 50 percent of Mexico's banks, but together, this group represents only 9.6 percent of the total assets of the Mexican banking sector. This means that this study leaves out all Domestic Systemically Important Banks (D-SIBs) that play a pivotal role in terms of competition. Moreover, Bhattacharya (2003) shows that a key limitation of the Bankscope database is the substantial overlooking of rural and very small banks.

⁵The duration of the reform effect is identified as the time elapsed (years) between the regime switch attributable to the financial reform and the next regime switch.

Traditional research on bank competition is based on either annual or quarterly data. In this regard, the use of monthly or more timely data to measure competition intensity offers a number of benefits for both policymakers and researchers. Policymakers are always looking for more timely indicators for monitoring purposes to facilitate prompt policy actions. In addition, a closer time interval provides a better opportunity to measure the impact of policy decisions. Our monthly estimates can alert policymakers about future events well ahead of time. Similarly, our findings can be useful for researchers who investigate the relationship between a bank's degree of competitiveness and its standalone risk benefit because risk may change significantly from one month to the next and quarterly data may fail to reflect this on a timely basis. It is convenient to develop measures that capture market overreactions or other shocks within the same time interval. Some shocks such as regulatory shocks may exert an effect on competition measures in the very short run, which may not be noticeable from low frequency data. Studies that investigate the relationship between loan pricing and competition at the bank level also benefit from a higher frequency, as changes induced by shocks in time-varying interest rates can be matched more accurately using monthly data. Specifically, consider the case of the impact that monetary policy decisions have on the pricing of time-varying interest rate loans at the time of loan origination or on outstanding loans and securitizations. Moreover, higher frequency data may enhance the performance of any forecasting technique significantly. Compared to studies based on annual or quarterly data, researchers can better evaluate the impact of any shock with a monthly series because variation at a higher frequency offers a more timely scope to capture the evolution of any time series. More up-to-date information provides a reliable idea on the expected direction and magnitude of any change, and this may also serve as an early warning indicator.

Compared to other studies available in the literature, our empirical analysis includes a large number of banks that vary in terms of systemic importance, business model, and ownership structure (i.e., publicly listed and privately owned banks). In contrast to some papers in the literature (see de Ramon and Straughan (2019)), we include investment banks in our sample and refrain from limiting our analysis only to deposit-taking entities. The reason for doing this is because there are large banks that compete in both investment and deposit-taking activities. In our view, it is not possible, in practice, to compute reliable competition measures that distinguish adequately between investment and deposit-taking costs. For example, the Lerner index requires as an input the bank's cost, and it becomes impossible in the case of large banks to distinguish between the share of cost attributable to deposit-taking activities from investment activities. Since large banks compete in both activities, we believe that

it is best to include investment banks.⁶ We only consider banks with unconsolidated data, which are classified as commercial. We exclude Micro-Financing Institutions, Governmental Loan Institutions, Multi-Governmental Banks, Securities Firms, and Non-Bank Financial Intermediaries (NBFI). Although we do not include all banks of the Mexican banking sector due to multiple data processes, we regard the overall coverage of our sample as extremely satisfactory.⁷

Following Jakovljević et al. (2015), we assume that the reform or regulatory shock will have an effect on banks' operations and performance, which would inevitably lead to changes in the composition of the bank's balance sheet as well as the bank's efficiency. The value of the bank-level competition measures available in this study depend on some of the values of the bank's balance sheet items. Thus, any balance sheet recomposition is picked up and captured by these variables. As expected, the evolution of competition and the distributional impact of the 2014 financial reform depend on the measure under analysis. We report a number of findings. First, we use aggregate and bank-level regression analysis and find that according to the standard Lerner index, the Boone indicator, and the composite competition index, there is a significant positive average effect on competition, which is attributable to the financial reform. In contrast, we also find that there is no significant effect when we use the refined Lerner index. This result is new to the literature, as other similar studies have not reported this opposing view between Lerner indices (see de Ramon and Straughan (2016)). Second, we use bank-level quantile regressions and document that the reform has had heterogeneous effects that vary across bank types. Specifically, we find subtle or tenuous evidence of competition deteriorating in one of the quantiles of the D-SIBs' competition conditional distribution.⁸ Moreover, we also find that the effect on investment is mixed, while the evidence of an increase in competition intensity across non-DSIBs is strong.⁹ Third, the Markov switching analysis suggests that there is a period of high competition intensity after the financial reform. However, we identified heterogeneity in the duration of competition intensity that varies with each measure. Fourth, our monthly estimations are reliable in that their value

⁶As a robustness check, we verify that our results do not change when we exclude investment banks from our sample. The results are available in Appendix A and discussed in Section 5.1.4.2

⁷Overall, the share of banks included in our sample represents, on average, more than 97% of the total assets of the banking sector.

⁸We analyze seven quantile regressions, and we find that although all coefficients of regulatory interaction terms have a positive sign, only one is significant at the 5 percent level for the 25th percentile. This finding leads us to classify this evidence as subtle or tenuous.

⁹Six out of seven quantile regressions analyzed in this study have a negative and significant coefficient for the interaction term.

is similar to other studies. Fifth, following the literature, we support the view that traditional industrial organization (TIO) measures are not a good proxy to measure competition. Finally, we document that the presence of a D-SIBs group largely dominates the market in terms of market power in our sample. In essence, this group has benefited from wider margins.

The remainder of the paper is organized as follows: section 2 offers a concise literature review on competition and provides background information on the 2014 Mexican financial reform, section 3 describes the characteristics of our data, section 4 lists the competition indicators used in this study and the methodology adopted to estimate them, section 5 discusses the empirical results, and section 6 provides the conclusion.

2 Literature Review

The following section starts with a critical summary of previous literature on competition where we identify and classify research studies to show where our paper fits in. This is followed by a regulatory background on the Mexican financial reform.

2.1 Previous Contributions to the Literature

Following Leon (2015b), it is possible to classify the literature on the measurement of competition, depending on whether the measure belongs to the TIO theory¹⁰ or to the new empirical industrial organization (NEIO).¹¹ The traditional approach is based on Cournot's analysis of the so-called structure-conduct-performance (SCP) paradigm that argues that competition intensity deteriorates with an increase in market concentration. This approach is developed from oligopoly theory and leads to a static state where firms cannot earn abnormal profits by increasing the price of their product. In contrast, the NEIO approach intends to study the firm (bank) behavior to overcome the limitations of the static approach. This alternative approach intends to gain an understanding of the market dynamics of competitive rivalry. The first generation of NEIO measures is based on a static model of competition, and both the Lerner

¹⁰The TIO or structural approach is useful for measuring the intensity of competition using the market structure as the unit of analysis.

¹¹The NEIO approach analyzes the intensity of competition while taking into account the behavior of banks in the market.

index and the Panzar and Rosse H -statistic originated as a result. In turn, the Boone indicator was developed in the second generation of NEIO measures. There is a strand of literature that has reviewed the strengths and weaknesses of the TIO and NEIO indicators (see Degryse et al. (2009), Liu et al. (2013), and Leon (2015a)). There is a consensus in the empirical literature that competition measures are not perfect substitutes, as each of them has advantages and limitations. Thus, studies should consider as many measures as possible, as each of them incorporates a different feature of competition.

We identify three strands in the literature. Perhaps, the most popular of them is focused on assessing the relationship between competition and the absolute level of an individual bank's risk of failure (e.g., Allen and Gale (2004), Schaeck et al. (2009), Anginer et al. (2014), and Jiménez et al. (2013)).¹² The proposal under the “franchise-value” hypothesis (see Matutes and Vives (2000) and other references therein) is that in a less competitive market, greater market power allows banks to build larger capital buffers, protecting their franchise value in the process, and this promotes a more conservative business model that leads banks to adopt low-risk strategies. The underlying implication of this theory is that there is a positive relationship between increased competition and the bank's standalone risk. However, there is an opposing view: the risk-shifting paradigm that supports the idea that the relationship is negative, as banks in a less competitive environment could result in higher interest rates being charged and, thus, raise the credit risk of banks (see Boyd and De Nicolo (2005)). The main concern or challenge in this strand is to test empirically whether the “franchise-value” or “risk-shifting paradigm” hypothesis is practically applicable. As of today, there is no agreement on which of the two opposing views is true, as empirical results are mixed.

The second strand in the economic literature intends to evaluate the impact of bank competition on credit growth and access to financing sources (see Leon (2015a)). In principle, the “market power” view suggests that any lack of competition is detrimental to the banking industry because it may lead to higher costs in terms of both interest rates and fees for consumers of banking services along with lower access to financing sources. However, the opposing view (i.e., information hypothesis) is that more intense competition may have a negative impact on banks' possibilities to build and conserve long-term lending relationships (Petersen and Rajan (1995)) as well as banks' incentives to invest in information acquisition technology (Hauswald and Marquez (2006)). These two factors worsen individuals' access to financing. As in the competition-stability nexus, there is no consensus in the literature on

¹²A bank failure may or may not have an impact on the stability of the financial system.

the impact of competition on credit growth. Results vary depending on whether the sample is multi-country or single country. Moreover, using different measures of competition and costs or access to loans leads to controversial results, as there is no agreement on which is the proper way to measure each of these two factors.

The third strand addresses issues related to the measurement of the impact of regulatory or supervisory policies as well as structural and technological factors on banks' degree of competitiveness, efficiency, and behavior in the financial market. Our study is closely related to this strand. The research papers in this strand study a number of factors affecting competition, such as the development of globalization, deregulation, financial reforms, foreign banks' participation, and/or removal of bank entry restrictions or barriers, payment, settlement technology adoption, bank privatization, bank mergers, bank consolidation, and crisis periods. Most papers look at the impact using multiple competition indicators, and a few take into account the post-crisis period. Using multi-country data, Delis (2012) studies the banking competition-financial reform nexus and the quality of institutions on a large scale from 1987 to 2005. He finds that underdeveloped countries characterized by poor levels of transparency, rule of law, and bureaucratic quality fail to show more competitive conditions after the implementation of a financial reform. Li (2019) also use multi-country data to investigate the impact of bank regulation and supervision on a group of 23 emerging economies between 1996 and 2006. They find that more competitive banking sectors are characterized by higher concentration, fewer activity restrictions, fewer entry barriers, fewer foreign bank limitations, increasing capital strictness, official supervisory powers, fewer government-owned banks, higher private monitoring of banks, and broader deposit insurance coverage. de Ramon and Straughan (2019) look at the evolution of competition in the UK between 1989 and 2013. They find that deregulation of the deposit-taking sector did not have a long-term positive effect on competition. Our study is based on single country data and is related to de Ramon and Straughan (2019).

2.2 Regulatory Background of the Mexican Financial Reform

Broadly speaking, structural reforms are designed to increase productivity and support growth. Historically, the initial idea was centered on reducing barriers to promote efficient resource allocation for investment, employment, trade, competition, and product design to boost innovation. Emerging market economies (EMEs) have gone through different episodes of struc-

tural reforms (Spilimbergo et al. (2009)). The first phase of the structural reforms started with trade liberalization reforms developed in the 1980s as a result of the debt crisis witnessed during protracted multilateral and regional negotiations. The second phase appeared in the early 1990s with the opening and liberalization of the capital account and the domestic financial sector. The third phase focused on adopting market-friendly agricultural policies. Finally, in the second half of the 1990s, EME reforms addressed deregulation in the real sector (e.g., telecommunication and electricity sectors). Unfortunately, the pace of reform implementations was stalled until 2009 when the G20 met in Pittsburgh and released a strategy to implement a framework to promote strong, sustainable, and balanced growth based on the implementation of new structural reforms (see Kamel (2014)). In essence, the plan was to reform the following: (i) the international financial architecture; (ii) product market reform, including trade related measures; (iii) labor market policy; (iv) investment in infrastructure to enhance the quality of public goods; (v) tax policies and the quality of the government and institutions. As a result of this initiative, Mexico released an ambitious national reform package plan in 2013 known as “Pacto por México”.¹³

Throughout history, the Mexican banking sector has adapted to several processes as a consequence of the following list of events: nationalization in 1982; privatization in 1991; the “Tequila” exchange rate crisis in December 1994; a gradual reopening to foreign investment in 1995; a consolidation process characterized by several mergers starting 2000; a reform to the law of credit institutions in 2001 to remove bank entry barriers.¹⁴ In 2014, Mexico adopted a financial reform that was specifically designed to promote competition between financial intermediaries.¹⁵ According to COFECE (2014, pp.17-21)), the Mexican financial reform addresses market failures (i.e., imperfections) and restrictions to competition that arise as an outcome of the following: (i) asymmetric information issues that often characterize financial markets; (ii) limited product access or use; and (iii) limited access to financial services among low-income sectors of the population, among others. Regarding market failures, a key objective was to reduce or control the presence of the following: (i) economies of scale; (ii) sunken costs; (iii) economies of scope and multi-product enterprises; (iv) network

¹³As expected, other large emerging market economies (e.g., Brazil, China, India, Indonesia, and Turkey) also introduced national reform packages.

¹⁴This reform removed a 20% cap on the ownership of bank stocks, which allowed business groups that were not a part of the banking sector to create new bank entities (see Castellanos et al. (2013, p.58)).

¹⁵The financial reform design was made to affect the competition of banks and non-bank financial intermediaries. This paper studies reforms that had an impact on banking entities; it does not investigate individual or specific policies. Instead, we examine the impact of the reform as a bundle.

economies; (v) two-sided markets; (vi) switching costs; (vii) unnecessary regulatory costs.¹⁶

In Mexico, the Federal Economic Competition Commission (i.e., COFECE, the Spanish acronym) is the authority made responsible by constitutional mandate for enforcing the Federal Economic Competition Law. This applies to all sectors of the Mexican economy, including the financial sector. Notwithstanding this, there are other public financial authorities¹⁷ that have powers to intervene if competition conditions in the sector worsen or if there is any risk factor (e.g., large merger) that may hinder competition.

Moreover, the 2014 financial reform mandated that COFECE was to conduct and submit an evaluation (i.e., a market study)¹⁸ to assess the state of competition, efficiency, and consumer welfare in the financial sector. COFECE released a document with 36 recommendations related to five types of conducts, which may be summarized as measures to do the following: (1) reduce barriers to entry; (2) avoid displacements or access deterrence for competitors in the financial market; (3) diminish the risk of collusion or coordinated effects among competitors; (4) prevent and eliminate restrictions to market efficiency; and (5) increase COFECE's effectiveness in sanctioning conducts that violate antitrust law.¹⁹

Broadly, the financial reform introduced a set of measures designed to promote activity between the following four fundamental areas: (i) stimulate the growth of lending by reducing the legal framework for compliance purposes in contracts so that banks can grant loans more easily; (ii) use contributions to reduce banks' rates and expenses; (iii) establish a new chain of supervision and regulatory powers as well as a new structure to foster development of the banking sector; (iv) strengthen financial authorities' legal powers to impose penalties;

¹⁶See COFECE (2014, pp.17-21) for details and full description of each of these market failures.

¹⁷The other authorities are the following: the Central Bank (BANXICO, its acronym in Spanish); the Ministry of Finance (SHCP, its acronym in Spanish); the National Banking and Securities Commission (CNBV, its acronym in Spanish); the National Insurance and Bonding Commission (CNSF, its acronym in Spanish); the National Retirement Savings System Commission (CONSAR, its acronym in Spanish); the National Commission for the Protection and Defense of Financial Services Users (CONDUSEF, its acronym in Spanish). The Financial Services Transparency and Regulation Law (LTSOF, its acronym in Spanish) has the regulatory framework that serves to coordinate the work between these financial authorities. According to LTSOF, authorities may regulate activities based on COFECE's opinion. For example, BANXICO has the power to assess if there is a reasonable level playing field for banks' liabilities (e.g., funding sources such as customers' demand or savings deposits) and active (e.g., price of loan granting) operations.

¹⁸A summary of this study in English is available at https://www.Cofece.mx/Cofece/images/Estudios/ExecutiveSummary_10022015.pdf; accessed on 29 July 2020

¹⁹For details, see the OECD report available at https://www.cofece.mx/wp-content/uploads/2018/03/2017_cooperacion-sector-financiero.pdf, accessed on 29 July 2020.

(v) ensure that the relationship between debtors and creditors is properly rooted in equity.²⁰ In a nutshell, the reform's key objective was to increase financial deepening by promoting competition and streamlining bankruptcy procedures. Specifically, the reform introduced a number of provisions to stimulate account portability for both credit and checking account to allow bank customers to switch between banks more easily. It also strengthened the legal framework for consumer protection. Furthermore, the reform strengthened banks' rights by assigning specialized courts to allow faster recovery of the collateral in the case of mortgage default. Additionally, the role of development banks was strengthened to foster the granting of both loans and loan guarantees to small and medium enterprises and small agriculture producers.

The main challenge in assessing the impact of the financial reform on the TIO and NEIO indicators is the fact that each competition or financial stability measure may have a different date of enforcement. Moreover, it is extremely difficult (if not impossible) to assess the individual impact of each measure and disentangle the impact of the interaction between any two or more measures.

3 Data Set

Our empirical analysis employs proprietary microeconomic data collected by Mexican financial authorities (i.e., BANXICO and CNBV) as well as publicly available macroeconomic and accounting information from commercial banks and regulated multiple purpose financial companies (SOFOMES, the acronym in Spanish) data.²¹ In this paper, we do not include entities such as credit unions or popular credit and savings entities because these compete to attract customers (e.g., micro-loans) using a business strategy that departs significantly from the activities of traditional commercial banks. Our analysis includes all banks operating in the Mexican banking sector from January 2008 to March 2019. We do not include SOFOMES as standalone entities. Instead, we use the consolidated data of banks with each of their SOFOME. In this paper, we assess the competition between entities that compete both in the traditional and non-traditional financial intermediation markets. We believe that

²⁰Essentially, these refer to bank resolution measures and liquidation procedures for strengthening public confidence in the stability of the financial system.

²¹SOFOMES are intermediaries that originate any loan type but cannot take public deposits. See Appendix A.1 for details.

this approach makes sense due to the fact that the greatest limitation of all NEIO competition measures is that they all assume that banks offer homogeneous goods and services (see Leon (2015b)).²² There are a number of mergers²³ that took place 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 (2019)). For any merger between any two banks, we follow the standard practice in the literature, i.e., we include individual data for both entities until the date of the merger and only the data for the new merged entity afterward. Thus, we “create” a new entity and stop tracking the information for the two individual bank entities. For the case of a 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 incorporates the accounting information of the SOFOME. In this paper, we exclude banks that had less than 24 months of data as well as those where we found a consistency issue with the reported time series.^{24,25} Overall, we have an unbalanced panel with 43 banks for the period from January 2008 to March 2019 (i.e., 135 time periods).

In Mexico, banks are requested to fill pre-set regulatory layouts known as ‘R01-Minimum Catalogs’ each month.²⁶ In these layouts, banks register all of their operations that are related to their financial position in standard balance sheet items such as asset, liability, and capital. The ultimate regulatory objective is to follow or monitor the financial health of each bank and the structure of its individual operations (i.e, any asset side operation such as any loan grant, buying or selling of securities or derivatives, or any liability side operation such as receiving deposits, issuing debt, or any other operation related to any capital instrument) with any counterparty independently of whether these are registered on the asset or liability side of the

²²Some studies in the literature (e.g., de Ramon and Straughan (2019)) exclude bank entities that do not compete in the traditional intermediation market. However, this approach may be biased because certain bank-specific variables that form a part of the NEIO competition measures, such as bank benefits of large entities, arise from bank activity in both markets. Since it is not possible to isolate the costs arising from each bank activity, we have decided to incorporate all bank entities irrespective of their business model.

²³Overall, we have two mergers in our sample, (see Appendix A.3 for details).

²⁴It is not strange that in the empirical literature, a few banks’ regulatory reports suffer from inconsistent values. 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 the period from 2000 to 2014.

²⁵We have not taken into account the following banks in our analysis (i.e., ABC Capital, Bicentenario, Banco Wal-Mart, Bankaool, Consubanco, Deutsche Bank, GE Money, ING Bank, Accendo Banco, Mizuho Bank, and BiAfirme).

²⁶See 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/%7B073CCF98-39BE-EC8F-E03E-6D4CFFC9FA1A%7D.pdf>; accessed on July 23, 2020

balance sheet. Each bank must ensure that the information reflects financial operations up to the last day of the month. The regulatory framework allows banks between seven and eight working days after the month-end to submit their information. In turn, BANXICO validates the information quality using internal processes and filters that are especially designed and continuously refined to promote information accuracy and reliability. Just as other central banks, BANXICO uses this information to elaborate internal reports and research studies and perform on-site supervisory visits. Any bank breach related to the failure of sharing the requested information on a timely basis is penalized by BANXICO with an administrative penalty (i.e., civil money penalty). In an extreme case, BANXICO may suspend all or some of its transactions with the financial intermediaries that infringe its law or any of the provisions resulting thereof.²⁷

BANXICO has the authority to reach out to the bank's business unit if it identifies any source of misunderstanding during the revision period. In so doing, BANXICO follows a set of criteria to amend information in order to ensure that the information quality is as accurate as possible. As a supplement to the validation process, if the bank discovers that there is any mistake in the submitted or historical information, then it is obliged to resubmit the amended data as soon as possible. Moreover, BANXICO publishes a guide with a calendar that defines submission dates for the current year. It is convenient to point out that a part of the information reported in these regulatory layouts is not publicly available.²⁸

Each bank must send the data on an entity on a stand-alone basis without consolidating information with any of its foreign subsidiaries. In doing so, the information reflects all bank operations done in Mexico with either foreign or local counterparties. Regarding banks' foreign subsidiaries, they fill, on a stand-alone basis, a different section within the same regulatory layout. Submitted information must be consistent with the accounting criteria predetermined by CNBV.²⁹

The challenge of using monthly regulatory information is that some series, in a few cases, may have spikes or more variability than their annual or quarterly counterparts. To circum-

²⁷See article 37 of BANXICO's Law, which is publicly available at <https://www.banxico.org.mx/regulations-and-supervision/legal-framework/banco-de-mexico-law/%7B073CCF98-39BE-EC8F-E03E-6D4CFFC9FA1A%7D.pdf>; accessed on July 23, 2020

²⁸In our study, the single variable that is not publicly available is employees' remuneration (i.e., wages, salaries, or any other economic benefit such as bonuses or compensations).

²⁹It is convenient to point out that any operation in bank foreign currency must be reported in local currency using the exchange rate as conversion rate as prescribed in local accounting guidelines.

vent this, we smoothen our data using information related to the past twelve months. For example, the asset value for any bank in March 2014 is the average asset value of the past twelve months. Table A1 in Appendix A provides a list with the definition of each variable used in this paper along with their definitions and source. To minimize the impact of outliers, we use linear interpolation to substitute those values where the month-to-month change in logarithmic scale lies outside 1.5 times of its interquartile range (see Tukey (1977)).

Table 1 shows the composition of the Mexican banking sector at the bank level in our sample. Columns (1) to (3) of Table 1 show the minimum, average, and maximum value of the bank's market share based on total asset. The size of the bank's market share differs markedly depending on the bank's systemic importance. The largest D-SIB (i.e., BBVA Bancomer) has a maximum share value of 26.82 percent, while 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., Ixe and Interacciones) have a maximum market share value of 2.42 and 2.55 percent, respectively. Overall, we have 43 banks in our sample. Column (4) of Table 1 shows that 14 out of the 43 banks in our sample are foreign bank subsidiaries. Column (5) of Table 1 shows that there are nine D-SIBs³⁰ out of the 43 banks. A closer inspection shows that five out of the nine D-SIBs are foreign bank subsidiaries. Column (6) of Table 1 shows the bank entry status. Our sample initiates with 31 banks (e.g., Entry=1). During our sample period, 10 banks entered after January 2008 and received a bank license to operate in the banking sector (e.g., Entry=2), while two banks were virtually created as a result of a merger with two small banks (e.g., Entry=3).³¹ Column (7) of Table 1 shows that 39 banks remained in operation during our sample period (e.g., Exit=1), while four banks exited as a result of two mergers (e.g., Exit=2). Overall, the share of banks included in our sample represents, on average, more than 97% of the banking sector's total assets.

Table 2 shows a set of summary statistics for the key variables. Total costs range from \$0.13 billion to approximately \$175 billion with a mean value of \$16 billion and a median value of approximately \$4 billion. Total revenues vary even more as the range goes from \$0.06 billion to approximately \$240 billion with a mean value \$19 billion and a median value of approximately \$4.5 billion. As expected, the mean and median values of the ratio of revenues to cost are higher than one. The mean and median values of the return on assets are positive and equal to 0.01. In turn, the mean and median values of the ratio of profits to assets are

³⁰Two 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.

³¹This was due to the treatment of bank mergers where we identify any new merged entity as a new entity.

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

Bank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	Market share					D-SIB	Entry	Exit
	Min	Avg	Max					
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 Group (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	
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	

Source: Banco de México, authors' calculations.

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

also positive. The three input prices (i.e., $W_{it}^{(1)}$, $W_{it}^{(2)}$, and $W_{it}^{(3)}$) have a similar range from 0 to 0.43 with a similar mean value close to 0.04. With respect to other bank-level variables, the total assets range from \$0.34 billion to \$2,036 billion with a mean value of \$178 billion and a median value of approximately \$35 billion. The revenues to assets ratio range from 0.02 to 0.75 with a mean value of 0.15. There are large differences in banks' asset portfolio composition as shown by the expected loss performance (i.e., Loan loss provisions to total assets) that ranges from 0 to 0.17 with both mean and median values being equal to 0.02 and the unexpected loss performance (i.e., average risk weight) that can be as low as 0.13 with a median value of 0.63. As expected, the standard deviation of the unexpected loss performance measure is higher than that of its expected counterpart, as greater uncertainty is associated with determining the adequacy of the former. Loans to non-financial private firms and the households to assets ratio show that approximately 39% of banks assets are loans. This ratio may be zero because we include some investment banks that do not originate loans in our sample. The funding strategy of banks vary significantly, as the retail funding to liabilities ratio ranges from almost zero to one. On average, this ratio has a value of 0.50, while the 25th percentile suggests that at least 75% of the banks considered show the classic behavior of a deposit-taking institution. Regarding the state of the Mexican economy, during the period of our analysis, the economy has been growing at a moderate average annual rate of 2%; the unemployment rate has remained stable at 4%, while the inflation rate is a one-digit number that has varied from 2% to 7%.³²

4 Competition Measures and Empirical Strategy

In this section, we describe the indicators used in this paper as a proxy to measure competition intensity in the Mexican banking sector. In particular, we briefly summarize the findings of the analysis of three TIO or market performance-based concentration measures; then, we discuss our three primary NEIO measures.

³²Since 2003, the inflation targeting regime of BANXICO has been set by its Board at a 3% level with a variation margin of 1%.

Table 2: Descriptive statistics of micro and macro variables

Variable	Mean	Std Dev	Min.	Q. 25	Median	Q. 75	Max
Dependent variables							
Total costs ^a (C_{it})	16.07	29.02	0.13	1.22	3.85	13.42	174.87
Revenues to costs ratio ^b (RC_{it})	1.16	0.23	0.32	1.04	1.12	1.23	3.08
Total revenues ^c (TR_{it})	19.17	35.47	0.06	1.44	4.50	15.71	239.71
Return on assets ^c (ROA_{it})	0.01	0.03	-0.20	0.00	0.01	0.02	0.24
Profits to assets ratio ^d (π_{it})	0.02	0.04	-0.33	0.00	0.01	0.02	0.35
Independent variables							
<i>Input prices</i>							
Bank funding costs ($W_{it}^{(1)}$)	0.04	0.03	0.00	0.02	0.03	0.05	0.42
Bank labor expenses ($W_{it}^{(2)}$)	0.03	0.05	0.00	0.00	0.01	0.02	0.43
Operational costs ($W_{it}^{(3)}$)	0.04	0.07	0.00	0.01	0.02	0.04	0.43
<i>Other bank-level variables</i>							
Total assets (Q_{it})	177.91	345.08	0.34	14.68	34.88	115.82	2036.29
Revenues to assets ratio (P_{it})	0.15	0.14	0.02	0.08	0.10	0.15	0.75
Costs to revenues ratio (\hat{C}_{it})	0.89	0.17	0.32	0.81	0.89	0.96	3.15
Provisions to assets ratio (PR_{it}/Q_{it})	0.02	0.03	-0.00	0.01	0.02	0.03	0.17
Loans to assets ratio (L_{it}/Q_{it})	0.39	0.25	0.00	0.18	0.37	0.58	0.98
Retail funding to liabilities ratio (RF_{it}/LR_{it})	0.50	0.27	0.00	0.30	0.53	0.70	0.99
Average risk weight (ARW_{it})	0.67	0.31	0.13	0.45	0.63	0.82	2.22
<i>Macroeconomic variables</i>							
Economic growth (EG_t)	0.02	0.03	-0.08	0.02	0.02	0.03	0.08
Unemployment rate (UR_t)	0.04	0.01	0.03	0.04	0.04	0.05	0.06
Inflation rate (IR_t)	0.04	0.01	0.02	0.03	0.04	0.05	0.07

Source: Banco de México, authors' calculations

Notes: This table reports the monthly descriptive statistics of all micro and macro variables by mean, standard deviation, minimum, 25th percentile (i.e., Q.25) or first quartile, median, 75th percentile (i.e., Q.75) or third quartile, and maximum for the analysis period from January 2008 to March 2019. All the variables are unit free except total costs, total revenue, and total assets, which are reported in thousands of millions (i.e., in B or 10^9 or 'one thousand million' in North America) in Mexican pesos (i.e., MXN). There are 43 banks in our sample, and these can be grouped as follows: 7 out of 43 banks are D-SIBs, 5 out of 43 are investment banks, 16 out of 43 are mid-sized banks, and 15 out of 43 are specialized banks. Economic growth is defined as $\nabla_{12}(EAI_t)/EAI_{t-12}$ where EAI_t is the economic activity index (IGAE, its acronym in Spanish), while the inflation rate is defined as $\nabla_{12}(CPI_t)/CPI_{t-12}$ where CPI is the consumer price index.

a: This variable is used for the estimation of the standard Lerner index (see eq.(2)).

b: This variable is used for the estimation of the refined Lerner index (see eq.(11)).

c: This variable is used for the estimation of the Panzar-Rosse H -statistic (see eq.(23)).

d: This variable is used for the estimation of the Boone indicator (see eq.(16)).

4.1 TIO or Concentration Measures

Many types of concentration measures are available in the literature, which have been applied to the banking industry (see Bikker and Haaf (2002)). It is well known that measures of concentration have a different structure based on their design and weighting scheme (see Leon (2015b)). In this paper, we analyzed three popular measures that have been widely used in the literature: the number of firms, the concentration ratios (CR), and the Herfindahl-Hirschman index (HHI). The analysis of these measures is standard practice in the literature. In what follows, we summarize the main findings and refer the interested reader to Appendix A.3 for details. Figures A2, A3, and A4 in Appendix A show the description and evolution of the number of bank entities, the concentration ratio for the seven D-SIBs (i.e., CR_7), and

the *HHI* index, respectively.

We report that the number of banks increased consistently during our sample period. In particular, the number of banks increased from 27 in 2007 to 40 in mid-2016. There are two points in time where the number of banks decreased due to a merger between a D-SIB and a non-DSIB. Our two concentration measures show that concentration is improving at the sector level but at a very slow rate during the sample period. Overall, similar to other advanced and emerging markets, the Mexican banking sector is concentrated in seven large bank entities.

4.2 NEIO Indicators

In this section, we describe the three most popular NEIO indicators available in the literature: the Lerner index (i.e., with and without the stochastic frontier approach) and the Boone indicator. For completeness purposes, we also compute the Panzar-Rosse *H*-statistic (see Panzar and Rosse (1987)) for the Mexican Banks over the period from 2008 to 2019. The results are available in Appendix A.6³³

4.2.1 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. A signal of 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 NEIO competition measures is that it yields an individual bank measure of market power (Degryse et al., 2009). The Lerner index is defined as follows:

$$L_{it} = \frac{P_{it} - MC_{it}}{P_{it}}, \quad (1)$$

where L_{it} denotes 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 the bank's total interest

³³This indicator has a number of shortcomings, and its sector value is limited compared to other measures, as it does not vary over time.

and non-interest revenue per output unit as a proxy for P_{it} , and we use the bank's total assets as a proxy for the bank's output. In practice, the challenge is to estimate the unobservable marginal cost function of the bank. Due to its complexity, we propose the use of a standard estimation framework, and then we analyze a refined approach. The latter takes into account the role played by potential optimization errors in the cost function minimization. Moreover, the refined approach takes into account that banks may not have constant returns to scale.

4.2.1.1 Lerner Index: Standard Approach

According to Berger et al. (2009), Beck et al. (2013) and de Ramon and Straughan (2019), the standard approach involves estimating marginal costs from the estimated parameters of a translog single output-cost function. The rationale behind this approach is that banks have to fund their assets using deposits, and to do so, they incur production costs associated with interest and staff expenses along with other operational costs. The estimated translog total cost function is defined as follows:

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

where C_{it} is the total cost for bank i at time t , α_i and η_t are the parameters used to control for both bank and time fixed effects,³⁴ respectively, Q_{it} is proxied by the bank's total asset, $W_{it}^{(1)}$, $W_{it}^{(2)}$, and $W_{it}^{(3)}$ are the interest, labor, and fixed expense (i.e., operational costs) input prices that are proxied by the ratios of interest expense, labor expense, and operational expense to total assets, respectively. Moreover, we include a set of constraints³⁵ 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 bank-level to allow for intra-group effects. Finally, to calculate the marginal cost, we

³⁴Bank fixed effects are used to control for bank heterogeneity. In turn, time fixed effects are used to control for business cycle variation and technological progress. This approach was originally introduced by Berger et al. (2009) and subsequently used by Beck et al. (2013). de Ramon and Straughan (2019) adopts an alternative framework to estimate the same cost function, which differs in that it includes macroeconomic variables and omits time fixed effects.

³⁵The three coefficient constraints are as follows: i) $\sum_{k=1}^3 \gamma_k = 1$, ii) $\sum_{k=1}^3 \phi_k = 0$, and iii) for all k , $\sum_{j=1}^3 \delta_{kj} = 0$.

differentiate eq.(2) and use the estimated parameters of eq.(2) as follows:

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

This is a time-varying bank-specific measure that allows researchers to compare the individual market power between banks. By definition, the Lerner index should be positive because P_{it} should be greater or equal to MC_{it} . However, in practice, neglecting the presence of banks' inefficiencies (i.e., individual bank's optimization errors due to cost function minimization) may lead to negative values in a few cases. This version of the Lerner index assumes that banks have constant returns to scale (see Bresnahan (1989)).³⁶ The Lerner index for the banking sector of any country at any time period t can be computed as follows:

$$L_t = \sum_{i=1}^n \omega_i L_{i,t} \quad (4)$$

where L_t is the Lerner index of bank i , and ω_i is the market share that can be proxied by the bank's asset, deposit, or the size of the bank's loan portfolio to the private non-financial entities. An unweighted Lerner index assumes that all banks have the same relative importance and that this is equal to $1/N$.

4.2.1.2 Lerner Index: Refined Approach

The refined approach to estimate the Lerner index had its origin in the econometric stochastic frontier analysis developed by Kumbhakar and Lovell (2003) and Kumbhakar et al. (2012). Moreover, Coccorese (2014) recently applied this framework to the banking industry. This approach has three advantages, compared to the standard alternative: (i) Banks may not be efficient when they minimize their cost function (e.g., optimization error), and this has to be taken into account when estimating the mark-up process; (ii) It also guarantees that negative values in the Lerner index will not occur Kumbhakar et al., (2012, p.113); (iii) It considers that banks may not have constant returns to scale. In other words, the refined and standard Lerner indices imply different assumptions in terms of bank's efficiency. The main underlying assumption of the standard Lerner index estimation process is that banks are efficient. In contrast, the refined Lerner index takes into account that banks may not be efficient. In fact,

³⁶It is convenient to point out that the Lerner index is a versatile measure that can be used to study the effect of network externalities in the banking sector (see Pontual Ribeiro and Golovanova (2020) for an application). In this paper, we do not address this issue.

the refined Lerner index takes into account the optimization error or divergence between the bank's optimal choice (i.e., the one that maximizes profit or minimizes costs) and its actual non-optimal election.

Any bank optimizing its profit must have a price greater than its marginal cost (i.e., $P_{it} \geq MC_{it}$). Kumbhakar and Lovell (2003) and Coccoresse (2014) show that if we multiply both terms of the price-marginal cost inequality by the ratio of Output ($Q_{i,t}$) to Total Cost ($C_{i,t}$), it leads to the following:

$$\frac{P_{i,t}Q_{i,t}}{C_{i,t}} \geq \frac{\partial C_{i,t}}{\partial Q_{i,t}} \frac{Q_{i,t}}{C_{i,t}} \quad (5)$$

or

$$\frac{TR_{i,t}}{C_{i,t}} \geq \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} \quad (6)$$

where $TR_{i,t}$ is the bank's total revenue. Rewriting eq.(6) leads to the following:

$$RC_{i,t} \geq \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} \quad (7)$$

where $RC_{i,t}$ is the bank's revenue share to total costs for bank i at time t , while the ratio of partial derivatives of logarithms is the cost elasticity with respect to the output $E_{C,Q}$. Aigner et al. (1977) and Meeusen and van Den Broeck (1977) show that this equation can be interpreted as a stochastic frontier model:

$$RC_{i,t} = \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} + v_{i,t} + u_{i,t} \quad (8)$$

where $\frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} + v_{i,t}$ is the minimum level that $RC_{i,t}$ can reach (the stochastic frontier), $v_{i,t}$ is a symmetric (two-sided) noise term that has to be included to take into account the impact of unobserved factors to the revenue-cost ratio³⁷, and $u_{i,t}$ is a measure of mark-up (Kumbhakar et al., 2012). We assume that the total costs can be estimated using a translog total cost function in which the usual symmetry and linear homogeneity in input prices are imposed by dividing total costs by one of the input prices. Here, we choose $W_{it}^{(3)}$. Therefore, the translog function can be expressed as follows:

³⁷This term also needs to be included because it takes into account the optimization error or divergence between the bank's optimal choice (i.e., the one that maximizes profit or minimizes costs) and the actual observed choice.

$$\begin{aligned}
\log(C_{it}/W_{it}^{(3)}) = & \alpha_0 + \alpha \log(Q_{it}) + \frac{1}{2} \beta \log(Q_{it})^2 + \\
& \sum_{k=1}^2 \gamma_k \log(Q_{it}) \log(W_{it}^{(k)}/W_{it}^{(3)}) + \eta T \log(Q_{it}) + \\
& \sum_{k=1}^2 \phi_k \log(W_{it}^{(k)}/W_{it}^{(3)}) + \frac{1}{2} \sum_{k=1}^2 \sum_{j=1}^2 \delta_{kj} \log(W_{it}^{(k)}/W_{it}^{(3)}) \log(W_{it}^{(j)}/W_{it}^{(3)}) + \\
& \sum_{k=1}^2 \kappa_k T \log(W_{it}^{(k)}/W_{it}^{(3)}) + \omega T + \frac{1}{2} \lambda T^2, \tag{9}
\end{aligned}$$

where $C_{i,t}$ are the total costs of bank i at time t , Q_{it} are the total assets of bank i at time t , $W_{it}^{(k)}$ are the three input prices for labor, interest, and operational expenses, and T is a deterministic time trend that controls for technological change and business cycle conditions. If we derive the previous equation with respect to output, we get the cost elasticity:

$$E_{C,Q} = \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} = \alpha + \beta \log(Q_{it}) + \sum_{k=1}^2 \gamma_k \log(W_{it}^{(k)}/W_{it}^{(3)}) + \eta T. \tag{10}$$

Substituting eq.(10) in eq.(8) leads to the following:

$$RC_{it} = \alpha + \beta \log(Q_{it}) + \sum_{k=1}^2 \gamma_k \log(W_{it}^{(k)}/W_{it}^{(3)}) + \eta T + u_{it} + v_{it}, \tag{11}$$

where RC_{it} is the ratio of total interest and non-interest revenue to total costs for bank i at time t , u_{it} represents the inefficiency, which is assumed to follow a half normal distribution, and v_{it} is the error term (see Aigner et al. (1977) and Meeusen and van Den Broeck (1977)). To estimate this equation, we use the stochastic frontier method with unobservable heterogeneity (i.e., true fixed effects) originally proposed by Greene (2005) and improved later by Chen et al. (2014) and Belotti and Ilardi (2018).³⁸ As in the standard case, our baseline model is estimated with both bank fixed effects and clustered standard errors by individual bank. Finally, if we multiply both sides of eq.(8) (i.e., omitting the error term) by $1/E_{C,Q} = 1/\frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}}$,

³⁸Greene (2005) shows that his approach could lead to inconsistent variance estimates that affect the estimation of the inefficiencies. Therefore, we use the estimators proposed by Chen et al. (2014) and Belotti and Ilardi (2018), which eliminate the fixed-effects by applying a first-difference transformation to the data and estimate the resulting model by marginal maximum likelihood.

rearrange terms, and use the fact that $RC_{i,t} = TR_{i,t}/C_{i,t}$, we get the following:

$$\frac{TR_{i,t}}{C_{i,t}} \left(1 / \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} \right) = 1 + \frac{u_{i,t}}{E_{C,Q}}. \quad (12)$$

Given that $TR_{i,t} = P_{i,t}Q_{i,t}$ and that $\frac{TR_{i,t}}{C_{i,t}} \left(1 / \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} \right) = \frac{P_{i,t}Q_{i,t}}{C_{i,t}} \left(1 / \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} \right) = \frac{P_{i,t}}{MC_{i,t}}$, if we substitute the previous equality on the left hand side of eq.(12) and subtract one, we get the following:

$$\frac{P_{i,t} - MC_{i,t}}{MC_{i,t}} = \frac{u_{i,t}}{E_{C,Q}}. \quad (13)$$

Let $\theta_{i,t} = (P_{i,t} - MC_{i,t})/MC_{i,t}$. Then, the Lerner index can be computed as follows:

$$L_{it} = \frac{\theta_{i,t}}{1 + \theta_{i,t}} = \frac{u_{i,t}}{E_{C,Q} + u_{i,t}}, \quad (14)$$

where $u_{i,t}$ denotes the mark-up term and $E_{C,Q}$ is the elasticity of total cost to output term, which can be derived or fitted from the deterministic part of eq.(11).³⁹ Coccoresse (2014) also shows that the point estimate of $E_{C,Q}$ allows one to get a measure of returns to scale, by recalling the following:

$$E_{C,Q} = \frac{\partial \ln C_{i,t}}{\partial \ln Q_{i,t}} = \frac{MC_{i,t}}{AvgC_{i,t}}, \quad (15)$$

where $AvgC_{i,t}$ is the average cost. Then, the proxy of returns to scale is $1/E_{C,Q}$.

Coccoresse (2014) underscores that the analyst has to be sure that the economic theory is compatible with the assumption of the non-negativity of $u_{i,t}$. This is related to the assumption that banks maximize profit, and depending on the market, this implies that $P_{i,t} \geq MC_{i,t}$, which in turn implies the non-negativity of $u_{i,t}$. Nevertheless, one could argue that when banks report losses, this might not hold. However, when banks have losses, we have $P_{i,t} < AvgC_{i,t}$, which implies that $E_{C,Q} = MC_{i,t}/AvgC_{i,t} < 1$. The last inequality allows one to state that $u_{i,t}$ is non-negative as long as $E_{C,Q} < 1$, which is always true for a profit-maximizing firm. Bear in mind that $P_{i,t} \geq MC_{i,t}$ is true in the long run. However, certain situations in the short run might lead prices to fall below marginal costs.

³⁹See Kumbhakar et al. (2012) or Coccoresse (2014) for a detailed derivation of the equation used to estimate the refined Lerner index.

4.2.2 Boone Indicator

The rising popularity of the Boone indicator (see Boone et al. (2007), Boone (2008)) stems from its virtue of capturing market dynamics (i.e., the Boone indicator takes into account the aggressiveness of competitors' conduct in the market). The underlying principle is based on the idea that efficient banks achieve superior performance in terms of higher profits compared to inefficient banks. Moreover, in an intense competitive environment, this process may help efficient banks to attain a higher market share. In other words, this implies that in a competitive market, the profits of inefficient banks will be adversely affected compared to that of efficient banks. Due to this relation between profits and efficiency, the Boone indicator captures the so-called “reallocation effects”, that arise when efficient banks prosper at the expense of inefficient banks that eventually exit the market. Moreover, when the least efficient banks exit the market, the “reallocation effect” intensifies as it combines with the “selection effect”.

To estimate the Boone indicator, we follow Boone et al. (2007), Schaeck and Cihák (2014), Kick and Prieto (2015). According to their proposal, the Boone indicator is the β_t coefficient estimate⁴⁰ for each time period t from the following profitability equation:

$$\pi_{it} = \alpha_i + \gamma_t + \beta_t \log(\hat{C}_{it}) + \delta X_{it} + \varepsilon_{it}, \quad (16)$$

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 that take into account unobserved heterogeneity, \hat{C}_{it} is the ratio of the bank's cost to revenue, and X_{it} are bank-specific control variables. We use the following four bank specific ratios as control variables: provision to total assets, loans to non-financial private firms and households to total assets, retail funding to total liabilities, and average risk weights. The β_t coefficient in eq.(16) is the profit elasticity with respect to the average cost.⁴¹ We estimate this model using a twelve-month rolling window. Ideally, it is desirable to estimate equation eq.(16) in each time period (see Schaeck and Cihák (2014)). However, given that in our sample, there are months where there are less than 35 banks, we could lose valuable information, and this may lead to unreliable or incomparable estimations. An increase in the

⁴⁰In theory, the Boone indicator is expected to be negative because any increase in the bank's cost should decrease its profit. In this regard, a more efficient bank will have a β (i.e., Boone indicator) closer to zero. However, in practice, the Boone indicator may be positive when firms compete in quality (see Tabak et al. (2012)) and, in turn, in this unfortunate case, identification is impossible.

⁴¹The profit elasticity measures the percentage decrease in the bank's i profit that arises when the cost of the bank's i cost increases by one percent.

Boone indicator signals that the competition is less intense in the banking sector as a whole.

It is possible that any bank's profit and cost are jointly determined. It could be even worse, as the most efficient banks may also be those having more market power, which leads to endogeneity concerns. Empirical papers use an instrumental approach to control for endogeneity. In this paper, to estimate eq.(16), we use a two-step generalized method of moments (GMM) estimator with clustered standard errors at the bank level. In this estimation method, the most challenging part is to identify a set of reliable instruments. We use up to the six-month lag of the cost to revenue ratio as instruments for the cost to revenue ratio.

5 Results

5.1 NEIO Measures

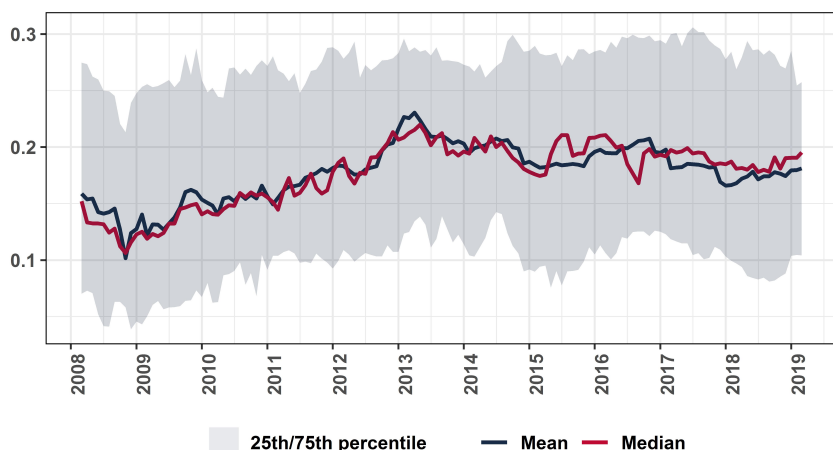
5.1.1 Lerner Index: Standard Approach

Figure 1 shows the evolution of the distribution of the unweighted individual bank Lerner index estimated using the standard approach.⁴² Specifically, we show the mean and median values across all banks that form a part of this study along with the interval between the 25th and 75th percentiles. The mean and the median of the Lerner index distribution show a similar behavior during the whole sample period. We identify four periods based on the trend of the mean and median values. First, during the period of the financial crisis between 2008 and 2009, there is a slight decrease in market power. Second, from 2009 to 2013, there is an increase in market power that reaches its global peak in 2013. Third, market power remains stable between the period from mid-2013 to end-2016. Finally, starting 2017, there is a downward trend, and the market power ends with a level similar to the one observed in

⁴²As a robustness test, Table A2 in Appendix A shows the estimation of the cost function for five alternative models: (i) time fixed effects with clustered standard errors (i.e., baseline case); (ii) time fixed effects with standard errors; (iii) time fixed effects with banks grouped by business model or specialization; (iv) pooled ordinary least squares; (v) macroeconomic variables with clustered standard errors, excluding time fixed effects. Figure A5 in Appendix A shows the unweighted Lerner index for the five specifications under analysis. Apparently, there is no difference in the overall trend to prefer any of the alternative versions with respect to our baseline model.

end-2012.⁴³ The distribution of the Lerner index as measured by the interval between the 25th and 75th percentile also changes over time and widens to its maximum value in July 2017. It is convenient to point out that the range of Lerner's mean and median values that vary between 0.1 and 0.23 aligns with values reported in the literature for this indicator in the banking sectors of advanced economies.^{44,45}

Figure 1: The evolution of the unweighted Lerner index distribution based on the standard approach



Source: Banco de México, authors' calculations

Notes: This figure shows the evolution of the Lerner index for each month in the period from January 2008 to March 2019. The blue line shows the mean value, and the red line shows the median value of the Lerner distribution. The shaded area marked as "25th/75th percentile" shows the interval between the 25th and 75th percentile of the distribution. An increase in the Lerner Index indicates an increase in bank's market power, and this is associated with a decrease in competition. The labels on the horizontal axis indicate the beginning of the year.

Figure 2 shows the distribution of unweighted Lerner indices grouped by bank type.⁴⁶ We

⁴³Even when the theoretical value of the Lerner index cannot be negative, in our estimates, we do observe negative values for some banks in a few months (i.e., 20 banks, all of them small), and the number of negative observations (bank-month observations) represent 8.55% of our sample. This happens because the Lerner index does not take into account the technical inefficiencies that could affect the mark-up of each banking firm (see Coccorese (2014) and de Ramon and Straughan (2019)).

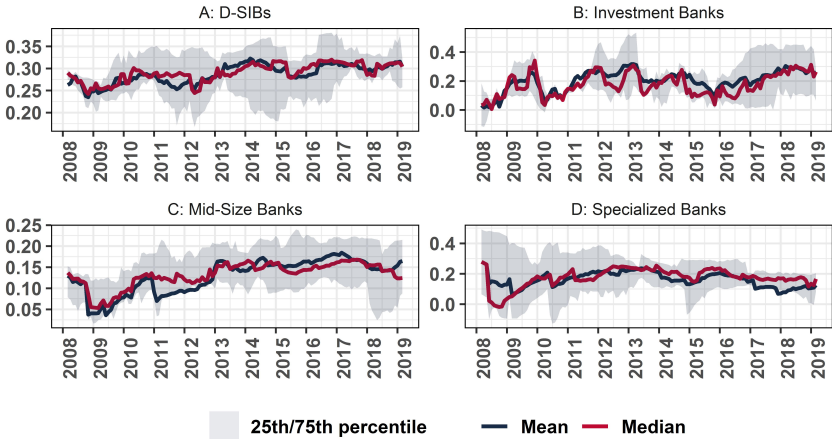
⁴⁴See de Ramon and Straughan (2019, p.10) for a sample of UK banks, Berger et al. (2009, p.109), Beck et al. (2013, pp.241-242) and Anginer et al. (2014) for a sample of international banks, Buch et al. (2013, p.1411) for a sample of German banks, and Maudos and De Guevara (2007, p.2113) for a sample of European banks. Moreover, our results are similar to those of a few Asian countries (e.g., South Korea, Hong Kong, and Taiwan) as reported by Soedarmono et al. (2011) for a sample of 12 Asian banks.

⁴⁵Figure A6, A7, and A8 in Appendix A show the evolution of the distribution of the weighted (e.g., total assets, private non-final loan portfolio, and total deposits) Lerner index for the sample period. As expected, the weighted mean and median of the standard Lerner index have greater values, as D-SIBs have more market power than non-DSIBs.

⁴⁶We group banks in four categories and follow a two-step procedure. First, we distinguish between D-SIBs and non-D-SIBs. Next, we differentiate the non-D-SIBs based on their activity and separate those that are focused on investment (i.e., investment banks), those that are focused on attending specific segments of the

report four noteworthy features. First, D-SIBs have greater mean and median values for their Lerner index for the whole sample period compared to non-D-SIBs. This is expected because D-SIBs have well-known comparative advantages (e.g., economies of scale, diversification, size, brand, and technology) in relation to non-D-SIBs that lead to a higher market power. Second, there is a very high variability even in the Lerner index within D-SIBs. Third, time series variability (i.e., as measured by the range of values of the mean and median) of the Lerner index is greater for non-D-SIBs.⁴⁷ Fourth, investment banks have the greatest time series variability (i.e., as measured by the range of values of the mean and median) of the Lerner index within non-D-SIBs. This is because, in practice, trading activity services are usually subject to more pressure in terms of competition than traditional banking services.

Figure 2: The evolution of the unweighted Lerner index distribution by bank type based on the standard approach



Source: Banco de México, authors' calculations
Notes: This figure shows the evolution of the Lerner index grouped by bank type for each month from January 2008 to March 2019. Panel A shows the evolution for D-SIBs, Panel B shows the evolution for investment banks, Panel C shows the evolution for mid-size banks, and Panel D shows the evolution for specialized banks. The blue line shows the mean value, and the red line shows the median value of the Lerner distribution. The shaded area marked as the “25th/75th percentile” shows the interval between the 25th and 75th percentile of the distribution. An increase in 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.

loan market (i.e., specialized banks), and those carrying a mix between these two (i.e., mid-size banks).
⁴⁷The range of values (i.e., the interval between the maximum and the minimum value) for the mean (median) of non-D-SIBs is as follows: investment banks show values ranging from 0.0166 (0.0061) to 0.3178 (0.3416), mid-size banks from 0.0360 (0.0530) to 0.1843 (0.1683), and specialized banks from 0.0676 (-0.0183) to 0.2786 (0.2698).

5.1.2 Lerner Index: Refined Approach

Figure 3 shows the evolution of the distribution of the unweighted individual bank Lerner index estimated using the refined approach (i.e., stochastic frontier analysis, see eq.(11)).⁴⁸ Specifically, we show the mean and median values across all banks that form a part of this study along with the interval between the 25th and 75th percentiles. While relatively stable over time, the values of the median of the Lerner index are not similar with the mean as in the case of the standard approach. This means that the heterogeneity is higher across the bank's Lerner index compared with the standard approach. Although the pattern of the trends is less clear than that in the standard case, we focus on the path followed by the median that is more robust to extreme outliers. Overall, we identify six periods. First, during the period between 2008 to 2010, there is a slight decrease in market power. Next, the median remains stable until mid-2012 when a sudden increase takes place until the beginning of 2013. The median decreases between 2013 and 2014, and after that, it remains stable until end-2016 and increases afterward. The mean and median values are lower compared to the standard approach, while the variability interval is more volatile in time (i.e., it shrinks and amplifies more widely). Interestingly, there is a decrease in the index over the whole sample period, which suggests that competition improved. This pattern differs from the standard approach where a worsening followed by an improvement in terms of competition intensity took place. As in Coccorese (2014), the estimation of the refined approach Lerner time series is smoother. As in the standard case, it is convenient to point out that the range of Lerner's mean and median values between 0.1 and 0.15 aligns with the values reported in the literature for this indicator in advanced economies' banking markets.^{49,50}

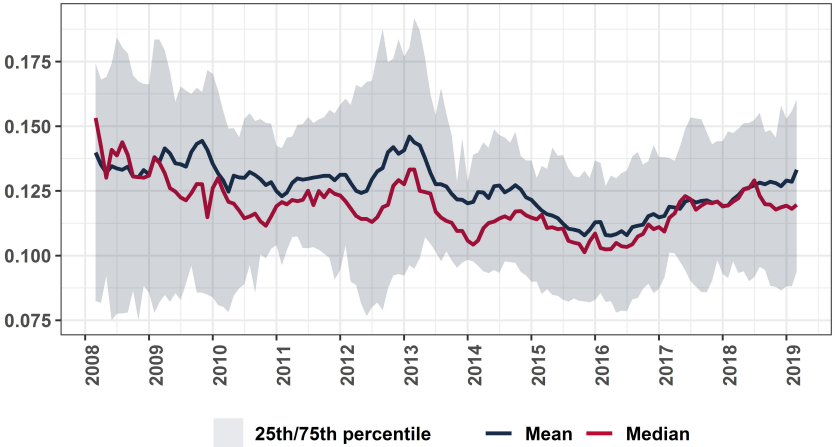
Figure 4 shows the evolution of the distribution of the unweighted Lerner index grouped by bank type. For the D-SIBs, there is a two-year period between 2013 and 2015 when the mean and median differ significantly. This means that the degree of heterogeneity heighten with respect to the standard case, and a few D-SIBs gain unconventional market power. As in the standard case, the D-SIB banks' Lerner index has a higher level for the whole sample

⁴⁸As a robustness test, Table A3 in Appendix A shows five alternative specifications used to estimate the refined Lerner index using eq.(11) as described in section 4.2.1.2. Our preferred choice is model M1 due to its simplicity. Figure A12 in Appendix A displays the evolution of the refined Lerner indices using different econometric specifications. In all the cases, the estimations follow a similar trend with comparable levels.

⁴⁹See Coccorese (2014, p.81) for a sample of international banks, including those in Mexico.

⁵⁰As in the standard Lerner index calculations, Figures A9 to A11 in Appendix A show the evolution of the distribution of the weighted (e.g., total assets, private non-financial loans portfolio, and total deposits) Lerner index for the sample period. The weighted Lerner indices have similar values to its unweighted counterpart.

Figure 3: The evolution of the unweighted Lerner index distribution based on the refined approach



Source: Banco de México, authors’ calculations.

Notes: This figure shows the evolution of the Lerner index for each month from January 2008 to March 2019. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. The shaded area marked as “25th/75th percentile” shows the interval between the 25th and 75th percentile of the distribution. An increase in 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.

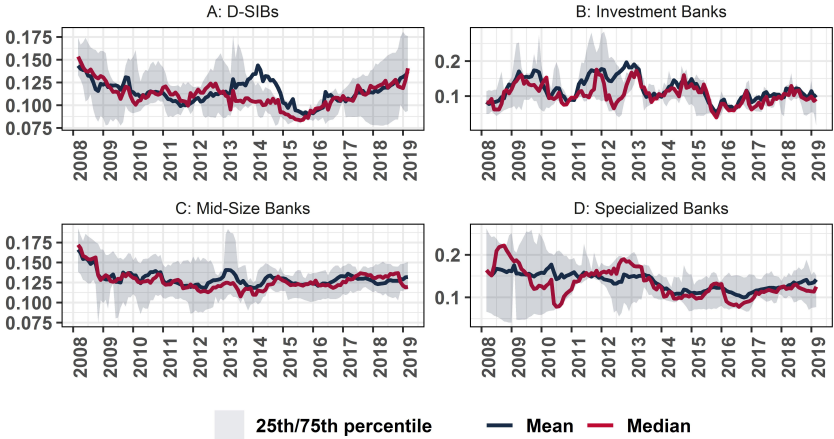
although investment banks also have higher levels. Mid-size banks’ Lerner index distribution remains mostly stable during the whole sample period. However, there is an increase in the market power of mid-size banks as measured by the interval between the 75th and 25th percentiles from 2013 to 2014. In turn, specialized banks display a huge level of heterogeneity from 2008 to early 2011.

5.1.3 Boone Indicator

Figure 5 shows the estimates for the Boone indicator as well as the 95% confidence interval. As in other empirical papers (see de Ramon and Straughan (2019)), our Boone indicator is negative for the whole sample period, and it is significantly less smooth than any of the other analyzed measures in this study. There is no defined trend for the whole sample period, but if we compare the starting with the end of the sample period, this indicator suggests that there is more intense competition. The values of this indicator decrease significantly after 2013, and this could be attributed to the financial reform.⁵¹

⁵¹Our Boone coefficient estimates have to be scaled by 100 to express them in percentage. This is useful if the reader wants to compare the values of our Boone indicator with those reported in the literature by de Ramon and Straughan (2019) for a sample of UK banks and Căpraru et al. (2020) for a sample of European countries.

Figure 4: The evolution of the unweighted Lerner index distribution by bank type based on the refined approach



Source: Banco de México, authors’ calculations.
Notes: This figure shows how the Lerner index distribution has evolved for different banking groups. Panel A shows the evolution for D-SIBs, Panel B shows the evolution for investment banks, Panel C shows the evolution for mid-size banks, and Panel D shows the evolution for specialized banks. The blue line shows the mean value, and the red line shows the median value of the Lerner distribution. The shaded area marked as “25th/75th percentile” shows the interval between the 25th and 75th percentile of the distribution. An increase in 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.

The estimation of the Boone indicator is based on a twelve-month rolling window regression and a two-step GMM estimator.⁵² To test the validity of our instruments, we use both the Sargan-Hansen *J*-test⁵³ and the Kleibergen-Papp Wald statistic.⁵⁴ In almost all rolling window regressions, we do not reject the null hypothesis of the Sargan-Hansen test.⁵⁵ In turn, the value of the Kleibergen-Papp Wald statistic for all our regressions is larger than the critical value of 19.28, which corresponds to a 5% maximal IV relative bias (see Stock and Yogo (2005)).

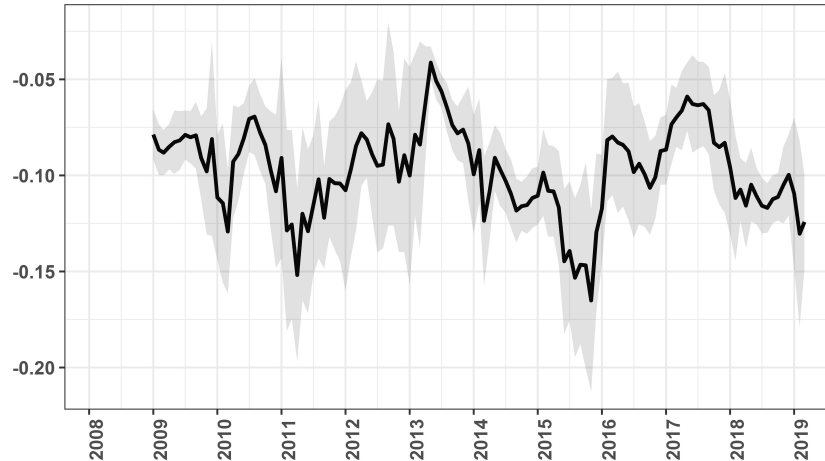
⁵²As a robustness test, we use Figure A13 in Appendix A to show the results for the Boone indicator estimated using different widths for the rolling windows. We also assess what happens when we remove bank-specific controls. We find that the estimated Boone indicators are highly correlated and follow a similar trend in relation to our baseline.

⁵³The objective of the Sargan-Hansen *J*-test is to assess whether the overidentifying restrictions are valid. The joint null hypothesis is that the instruments are uncorrelated with the error term and that the excluded instruments are correctly excluded from the estimated equation.

⁵⁴The objective of the Kleibergen-Papp Wald statistic is to evaluate whether the excluded instruments are weakly correlated with the endogenous regressors. The null hypothesis is that the instruments are weak.

⁵⁵In particular, in two time periods (i.e., May 2018 and September 2018), we have a significant *J*-statistic at the 5% level, and in only one time period (i.e., September 2011), we have a significant *J*-statistic at the 10% level.

Figure 5: Evolution of the Boone indicator



Source: Banco de México, authors' calculations

Notes: This figure shows the evolution of the estimated Boone parameter. The shaded areas are the 95% confidence interval around our estimates. An increase in the Boone indicator is associated with less intense competition. The labels on the horizontal axis indicate the beginning of year.

5.1.4 Robustness Test

In this subsection, we perform two robustness tests. We test what happens when we use quarterly data. Then, we also investigate what happens if we exclude investment banks from our sample.

5.1.4.1 Testing the Use of Quarterly Data

As a robustness test, we re-estimate all indicators using quarterly data, and the results are available in Appendix B.⁵⁶ The variables' definition is the same as the one presented for the monthly frequency. The descriptive statistics of the quarterly variables are shown in Table B1. Table B2 and B3 show the multivariate panel regression analysis for both the standard and refined Lerner indices, respectively. Figure B1 and B2 show the evolution of the standard Lerner index, while Figure B3 and B4 show the evolution of the refined Lerner index. Table B4 and B5 show the estimation results for the Panzar-Rosse H -statistic. Figure B5 shows the evolution of the Boone indicator. Finally, Table B6 shows the pairwise Pearson correlation matrix for all the analyzed competition measures.

We find that the Lerner indices' trends, patterns, or their levels broadly remain the same. Re-

⁵⁶As in the monthly case, we use the quarterly fixed effect where applicable.

garding the Panzar-Rosse statistic, we confirm our previous finding, i.e., competition between banks in Mexico is best characterized as monopolistic competition. In relation to the level and variation of the Boone indicator, quarterly results are very similar and almost identical to the monthly case. The only slight exemption occurs during early quarters. Finally, all the previous findings related to the pairwise correlation among NEIO competition measures remain the same with quarterly data.

5.1.4.2 Testing the Exclusion of Investment Banks from Sample

It is common practice in the economic literature to exclude investment banks from traditional banking inter-mediation services. Theoretical and practical advantages and disadvantages are associated with this procedure. The main advantage is that the production function assumes that banks produce a single good. The main disadvantage is that D-SIBs and other mid-size banks perform both activities (i.e., loan granting and investment), and it is not possible to differentiate in the data the relative share of each bank activity in some input variables such as the labor cost. To investigate whether including banks with different business models distorts our competition measures, we analyze what happens when we exclude investment and specialized banks from our sample.

Figure A19 in Appendix A displays the evolution of the unweighted standard Lerner index. Panel A shows the baseline model where all banks are included, irrespective of their type. Panel B shows the estimation where we include only D-SIBS. In this case, the behavior of the Lerner index differs with respect to our baseline. Moreover, the range of values (i.e., difference between the 75th and 25th percentile) of the Lerner index has more volatility. Panel C displays the estimation of the Lerner index excluding investment banks. In this case, the trend and levels of both the mean and median remain similar to our baseline; however, starting 2015, there is a greater divergence between them. Panel D excludes both investment and specialized banks. In this case, mean and median diverge between 2011 and 2013. Overall, we find that the level of the Lerner indices series is a bit lower in Panels B, C, and D.

Figure A20 in Appendix A shows the evolution of the unweighted refined Lerner index. Panel A shows the baseline model where all banks are included, irrespective of their type. Panel B shows the estimation while considering only D-SIBs. Compared to our baseline, we find a series with lower levels and similar trend, albeit more rough (i.e., less smooth) than the baseline. Panel C displays the estimations excluding investment banks. The evolution of the Lerner index is very similar to the baseline estimation; however, we observe a small

divergence between the mean and median from 2015 to 2018. Panel D shows the estimation excluding investment and specialized banks. As in the standard case, the overall trend is similar to the baseline specification; however, there is a divergence between the mean and median from 2011 to 2013. In general, we find that the level of the Lerner indices is a bit lower in Panels B, C, and D.

Overall, we conclude that it is best to include all banks in the case of a small, open, emerging economy characterized by a relatively small and well-capitalized banking sector. This result may not hold in more developed banking sectors.

5.1.5 The Crisis, Post-Crisis, and the Financial Reform

In this subsection, we determine whether the 2014 financial reform had an impact on the intensity of our NEIO competition measures. We treat the global financial crisis as an external exogenous shock and use a binary indicator as a control variable.⁵⁷ Our approach sympathizes with the argument that reform implementation may take some time to generate the intended effects. We propose a regression methodology to quantify the average annual change in the competition indicator induced by the financial reform. This approach is consistent with the financial reform literature that focuses on how factors change over time (see Hlaing and Kakinaka (2018)). We have strong and sound statistical and econometric reasons to believe that this approach is more appropriate and reasonable than trying to quantify what is the average actual impact on the level of the competition indicator during our sample period.

5.1.5.1 Linear Regression Analysis at the Aggregate Level

To test whether the financial reform had an effect on our competition measures, we estimate a simple aggregate linear econometric model as follows:

$$\nabla_{12}y_t = \alpha + \delta_1 D_{1t} + \delta_2 D_{2t} + \beta X_t + \varepsilon_{it}, \quad (17)$$

where $\nabla_{12} = (1 - L^{12})$ is the twelve-month difference operator (L is the lag operator) that uses (y_t) either the aggregate mean or median of (i) the standard, or (ii) refined Lerner index,

⁵⁷Our sample period excludes the period before the global financial crisis. It is compulsory to test the pre-crisis data if there is any change in the long run trend due to this event; hence, we only control for it.

or (iii) the Boone indicator as a dependent variable; α is a constant term; D_{1t} is a dummy variable to capture the crisis period that takes value one from 2008:M01 to 2009:M12; D_{2t} is a dummy variable to capture the post-financial reform period that takes value one from 2014:M01 to 2019:M03; X_t is a set of three macroeconomic control variables (i.e., economic growth, inflation rate, and the twelve-month difference in unemployment rate) used to account for business cycle conditions.

The annual difference operator in the linear regression analysis has been taken to identify specifically in a reliable way whether there are any changes in the competition trend that could arise as a result of a regulatory shock such as a financial reform. Lagarde (2012) uses an interrupted time-series framework⁵⁸ originally developed by Grimshaw et al. (2003) to illustrate how to measure the effect of an intervention at a precise point in time when other approaches, such as the randomization or identification of a control group, cannot be applied. Lagarde (2012) use a set of four simple graphic illustrations created from hypothetical data to explain the importance of accounting for three specific properties (e.g., stationarity, seasonality, and autocorrelation) of time series data. In a nutshell, Lagarde (2012) shows that it is not adequate to run an ordinary linear regression model with variables measured in levels when the dependent variable has an upward or downward trend (i.e., non-stationary time series) if the objective is to assess the effect of an intervention. The problem of using variables in levels is that the parameters are biased and the inference and findings are misleading (i.e., spurious inference process). This issue can be best explained as follows. In the time series analysis, dummy variables are used to capture differences or changes in levels. Assume that the dependent variable measured in levels has an upward or a downward trend during the sample period. Then, if we split the sample before and after the intervention and use dummy variables to estimate the mean of the post-intervention sub-sample, we will identify either a positive or a negative significant coefficient that falsely suggests that the intervention had an impact when, in fact, nothing happened. This problem persists even when the variable support is bounded in the $[0,1]$ interval, especially when an upward or a downward trend is observed over the sample period.⁵⁹ Moreover, variables measured in difference are free from any seasonality effect. To control for heteroscedasticity and autocorrelation in our inference

⁵⁸This approach has been used in financial economics by Ho and Wan (2002).

⁵⁹To provide evidence that the regression should not be estimated using variables measured in levels, Table A10 in Appendix A shows the results of performing univariate unit root tests for all variables used in eq.17, including residuals. We cannot reject the presence of a unit root process in the dependent variables when variables are measured in levels. In contrast, we reject the presence of a unit root process when dependent variables are measured in annual change. This result also applies to our control variables and the corresponding regression residuals.

process, we use heteroskedasticity and autocorrelation consistent (HAC) robust standard errors estimates (see Newey and West (1986)).

This provides convincing evidence supporting the use of the annual difference operator. Moreover, using the annual change of the competition measure rather than the indicator measured in levels is consistent with the objective of assessing how the reform affects annual competition changes over time rather than what is the effect at a given point in time. To some extent, measuring the dependent variable in difference is adequate if we perceive competition as a slow gradual process that takes some time to change. This approach is consistent with the argument that it takes time for the reform implementation to exert an impact on competition.

The regulatory binary indicator variable is designed to track any structural or long-term effect introduced by the financial reform on the expected annual changes in competition during the post-reform period. Thus, this approach will be characterized by a statistically significant coefficient if the financial reform is presumed to have affected competition in the banking sector. Naturally, we expect that the financial reform will enhance competition, and this will be indicated in our regression by a negative and statistically significant coefficient for D_{2t} . In our framework, we assume that the financial reform is an exogenous internal regulatory shock.

In this research, the global financial crisis period is treated as an exogenous external shock that may lead to atypical data or outliers during its duration. Additionally, our econometric regression model incorporates a set of local macroeconomic variables to control for other factors that could affect competition in the banking sector. The macroeconomic control variables incorporated in our analysis are also introduced as annual changes or in annual difference to mitigate any statistical time series concerns related to non-stationarity, auto-correlation, and seasonality (see Lagarde (2012)). It is also intuitively appealing, albeit not compulsory, to use exogenous variables measured in annual change to assess marginal effects.⁶⁰

Table 3 shows the estimation results of eq.(17). We focus on the significance and sign of the dummy variable to test if the financial reform had any impact on our competition measures. We find evidence that the 2014 financial reform period affected competition in the case of the standard Lerner index as well as for the Boone indicator. The negative sign of the coefficient suggests that the annual variation in the mean aggregate standard Lerner index decreases by

⁶⁰It makes more sense to assess the effect of a one-unit increase in the annual variation of GDP rather than analyzing the impact of a one-unit increase in GDP.

0.026 units on average. To put this result into perspective, in Table 4, we show the descriptive statistics for the competition variables measured in levels and in annual change. A decrease of 0.026 units in the mean aggregate standard Lerner index is slightly greater in absolute value than a one standard deviation change (0.02), and it is almost of half the size of its historical minimum decrease (0.04). This finding suggests that the average outcome from an annual increase in competition due to the financial reform is high, significant, and relevant. Likewise, the 2014 financial reform leads, on average, to an annual variation decrease of 0.03 units in the Boone indicator. Table 4 suggests that this reduction is similar in magnitude to a one-standard deviation in terms of absolute value, but it is half the size of its historical minimum (-0.06). Overall, these two indicators suggest that the financial reform has been relevant, as competition intensity increased with the implementation of the financial reform.⁶¹ The Lerner index suggests that the average bank market power has decreased, while the Boone indicator suggests that competition has intensified.

It is somewhat surprising that the refined Lerner index is not affected. One possible reason to explain this outcome is that banks with lower market power became more efficient.⁶² Thus, according to the refined Lerner index, the reduction in the average bank's market power has been compensated by efficiency gains. This average bank characteristic persists throughout the sample period and hinders the possibility of identifying any effect stemming from the financial reform. The fact that the refined Lerner index shows no signs of improvements due to the financial reform deserves further study. This issue may be related to the so-called "quiet life hypothesis".⁶³ This hypothesis argues that banks with market power are more prone to or prefer to incur/operate inefficiencies instead of reaping monopolistic rents. The idea is to adjust the Lerner index for profit inefficiencies. According to this theory, banks with greater market power are less efficient.⁶⁴

We also find evidence that the crisis period is not significant for any of our competition measures.⁶⁵ It is possible to argue that this result is somewhat unsurprising in terms of competition due to the following four reasons. First, we do not have data for the pre-crisis period.

⁶¹In the case of the refined Lerner index (mean and median), the coefficient sign is negative, but it is not statistically significant.

⁶²The standard Lerner index assumes full efficiency in its estimation process.

⁶³See Koetter et al. (2012) for an application for a sample of U.S. banks.

⁶⁴In a forthcoming study, Batiz-Zuk and Lara (2021) study how to test the "quiet life hypothesis" in the Mexican banking sector. Results are not yet available, as this is a work-in-progress.

⁶⁵It is not possible to include the crisis period using the Boone indicator due to its estimation method. Specifically, we only have a few estimates of this indicator that were available at the end of 2009.

Hence, we cannot identify if competition was more or less intense during our actual period. Second, microprudential regulatory measures such as the limits on maturity mismatch in foreign currency for banking institutions limited bank solvency risk due to currency risk pressures.^{66,67} Third, macroprudential regulatory measures, such as the limits on inter-bank exposures, also contribute to mitigating potential sources of systemic risk that arise from contagion risk due to the sudden and unexpected individual bank insolvency. Finally, the fact that branches of foreign banks are not allowed in Mexico and that foreign banks can receive a license to operate in Mexico only as stand-alone subsidiaries that have to comply with a minimum capital level also mitigates the risk of insolvency. Overall, the survival of local banks and foreign banks' subsidiaries was isolated from the turmoil in global financial markets. A stable banking market promoted a period where a significant number of small banks entered the banking sector, while only one bank went into bankruptcy.⁶⁸

In this context, it is relevant to test if a composite competition index that incorporates the information content of the aggregate standard and refined Lerner indices along with the Boone indicator is affected by the financial regulatory reform.⁶⁹ Moreover, the use of a composite indicator synthesizes complex multi-variate variables into one single metric that is easier to understand (Saisana and Tarantola, 2002). We construct a composite competition index for the banking sector using principal components analysis. Specifically, we use the mean and median values for the annual difference of our three individual competition measures and choose the first principal component as composite competition index for the banking sector. Higher values of the index are associated with less competition. Results are available and fully described in Appendix A. We report that the first component (i.e., composite competition index) explains more (less) than half of the variation for the mean (median) competition index.⁷⁰ Our regression results based on the composite indicator provide evidence that the financial reform had a positive average impact on stimulating competition intensity in the banking sector.⁷¹

⁶⁶In contrast to other banks in emerging economies of eastern European countries that faced a currency crisis, these limits on maturity mismatch ensured that no bank in Mexico reported a foreign currency liquidity problem. As a result, no Mexican bank went into bankruptcy during the global financial crisis period.

⁶⁷Other microprudential regulatory measures at the bank level, such as the limits on lending to related counterparties, also contributed.

⁶⁸In mid-2014, a very small bank (Bicentenario) filed for bankruptcy. This bank operated during a short time period, and due to our data filters, it was excluded from our sample.

⁶⁹We thank an anonymous referee for highlighting that analyzing this composite indicator is relevant due to the opposite evidence between the standard and refined Lerner indices.

⁷⁰The first component based on the mean (median) value explains 53% (44%) of the variation in competition.

⁷¹Nevertheless, it is convenient to take this result with caution, as using composite indicators is not uncontro-

Table 3: Impact of the financial reform at aggregate level

Variables	Standard Lerner		Refined Lerner		Boone
	Mean	Median	Mean	Median	
Economic growth _t	-0.0006 (0.0019)	0.0004 (0.0015)	-0.0007 (0.0011)	-0.0005 (0.0008)	-0.0083*** (0.0023)
Inflation rate _t	-0.0059*** (0.0018)	-0.0014 (0.0024)	0.0041*** (0.0008)	0.0038*** (0.0009)	0.0022 (0.0041)
∇ ₁₂ Unemployment rate _t	-0.0004 (0.0056)	0.0045 (0.0053)	-0.0019 (0.0029)	-0.0069** (0.0033)	-0.0511*** (0.0086)
D _{1t}	-0.0147 (0.0284)	-0.0144 (0.0225)	-0.0019 (0.0117)	-0.0088 (0.0085)	
D _{2t}	-0.0260*** (0.0056)	-0.0221*** (0.0046)	-0.0023 (0.0033)	-0.0013 (0.0032)	-0.0306*** (0.0085)
α	0.0440*** (0.0104)	0.0239** (0.0111)	-0.0145** (0.0064)	-0.0151*** (0.0055)	0.0185 (0.0200)
Observations	121	121	121	121	111
R-squared	0.47	0.38	0.26	0.30	0.32
Wald-statistic	14.53***	8.24***	7.26***	8.11***	12.89***

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table shows the linear regression estimates to assess any impact on the NEIO measures of the competition (i.e., standard and refined Lerner index or Boone indicator) stemming from the 2014 financial reform. The model was estimated using a twelve-month difference operator for the dependent variables. We include the R-squared to assess the goodness of fit and the Chi² statistic to test the null hypothesis that all coefficients are equal to zero. D_{1t} for the Boone indicator is not reported due to sample restrictions. Specifically, due to its estimation framework, we only have a few observations of the Boone indicator available from mid-2009 onward. HAC standard errors are presented in parenthesis.

5.1.5.2 Linear Regression Analysis at the Bank-Level

As a supplement to our analysis, we test whether the financial reform had an effect on our competition measures at the bank-level. We estimate a simple linear regression panel model defined as follows:

$$\nabla_{12}y_{it} = \alpha_i + \delta_1 D_{1t} + \delta_2 D_{2t} + \beta X_t + \gamma \nabla_{12}Z_{it} + \varepsilon_{it}, \quad (18)$$

where $\nabla_{12} = (1 - L^{12})$ is the twelve-month difference operator (L is the lag operator) using as dependent variable (y_{it}) either the (i) the standard or (ii) refined Lerner index for each bank. The difference operator has been used to assess the effect of the financial reform over the long-run competition trend.⁷² As in the previous exercise, measuring the dependent variable

versial and free from criticism (see Saltelli et al. (2005), Zhou et al. (2010)). We believe that our application is free from these flaws related to principal component analysis (PCA).

⁷²We use the annual change disguised as difference operator to compare the value of a statistic for one month to that of the same month in the previous year (i.e., year-over-year). This is useful for removing seasonal effects that may appear in some variables. It is also useful to discern long-term trends.

Table 4: Descriptive statistics of competition variables measured in levels and annual variation

	Mean	Std. Dev.	Min	Q25	Q50	Q75	Max
Panel A: levels							
Mean standard Lerner index _t	0.18	0.02	0.10	0.16	0.18	0.20	0.23
Median standard Lerner index _t	0.17	0.03	0.11	0.16	0.18	0.20	0.22
Mean refined Lerner index _t	0.13	0.01	0.11	0.12	0.13	0.13	0.15
Mean refined Lerner index _t	0.12	0.01	0.10	0.11	0.12	0.12	0.15
Boone index _t	-0.10	0.02	-0.17	-0.11	-0.10	-0.08	-0.04
Bank-level standard Lerner index _t	0.18	0.15	-0.64	0.10	0.18	0.28	0.71
Bank-level refined Lerner index _t	0.13	0.06	0.01	0.09	0.12	0.15	0.54
Panel B: annual variation							
∇_{12} Mean standard Lerner index _t	0.00	0.02	-0.04	-0.01	0.01	0.02	0.06
∇_{12} Median standard Lerner index _t	0.01	0.02	-0.03	-0.01	0.00	0.02	0.05
∇_{12} Mean refined Lerner index _t	-0.00	0.01	-0.03	-0.01	0.00	0.01	0.02
∇_{12} Mean refined Lerner index _t	-0.00	0.01	-0.03	-0.01	-0.00	0.01	0.02
∇_{12} Boone index _t	-0.00	0.03	-0.06	-0.03	0.00	0.02	0.07
∇_{12} Bank-level standard Lerner index _t	0.01	0.12	-0.77	-0.03	0.01	0.05	0.71
∇_{12} Bank-level refined Lerner index _t	-0.00	0.06	-0.49	-0.02	0.00	0.02	0.44

Source: Banco de México, authors' calculations

Notes: This table reports the monthly descriptive statistics for aggregate and bank-level standard and refined Lerner indices as well as for the Boone indicator. The annual difference operator refers to the value of the variable at time "t" minus the value at time "t-12".

in difference is adequate if we perceive competition as a slow and gradual process⁷³ that takes some time to change⁷⁴; α_i are bank fixed effects; D_{1t} is a dummy variable used to control for the crisis period that takes value one during 2008:M01 to 2009:M12; D_{2t} is a dummy variable used to capture the financial reform period that takes value one during 2014:M01 to 2019:M03; X_t is a set of three macroeconomic control variables (i.e., economic growth, inflation rate, and twelve-month annual variation in unemployment rate) that account for business cycle conditions, and $Z_{i,t}$ is a set of bank-level controls used to account for bank characteristics.

Table 5 shows the estimation results of eq.(18). We focus on the sign and significance of the two dummy variables D_{1t} and D_{2t} . As expected, we find evidence that the crisis period had no impact, as δ_1 is not significant in any of the analyzed competition indicators. This result

⁷³A gradual process means that we expect to see tiny increasing or decreasing variations over time. In other words, we do not expect to see volatility clusters or jump-processes or external or internal abrupt regulatory shocks. A gradual evolution of competition refers to the average of the bank level competition measure under analysis. We recognize that there is large heterogeneity across individual bank level data, but the unconditional banking sector average is characterized by a smooth evolution as evidenced by the unconditional average of the standard or refined Lerner indices.

⁷⁴Moreover, regulation is designed to allow for phase-in periods to promote a gradual adoption process of new rules in the banking industry. The competition industry has gone through a gradual deregulation process during our sample period. This is based on expectation and confirmed empirically by the evolution followed by both the mean values of the standard and refined Lerner indices.

supports our previous findings. In contrast, the coefficient of the 2014 financial reform is statistically significant at the 1% level only for the bank level standard Lerner index. The size of the negative sign of the δ_2 coefficient suggests that competition intensity increased after 2014 in a similar way as in the aggregate case. The fact that δ_2 is not significant in the case of the refined Lerner index deserves further study.

5.1.5.3 Quantile Regression Analysis using Bank-Level Data

We measure the effect of the financial reform on the bank-level standard and refined Lerner indices using quantile regression techniques (See Koenker and Hallock (2001)). We also compare and contrast our estimates using standard linear regression analysis. The novelty is that we estimate an augmented model to consider how the regulatory shock influences different bank types that we classify in three groups: D-SIBs, non-DSIBs, and investment banks. Linear regression coefficient estimates are not representative of the entire conditional market power distribution in the presence of unobserved heterogeneity. In other words, quantile regression has the advantage of modeling non-linear relationships between variables that lie outside of the data mean, and it is designed to offer robust coefficient estimates relative to ordinary least squares regression.

We estimate the following model:⁷⁵

$$Q_p(\nabla_{12}y_{i,t} \mid BankType_{i,t,b}, D_{1t}, D_{2t}, X_t, Z_{i,t}) = \alpha_p + \varphi_{p,b}BankType_{i,t,b} + \delta_{p,1}D_{1t} + \delta_{p,2,b}D_{2t} \times BankType_{i,t,b} + \beta_p X_t + \gamma_p Z_{i,t} + \varepsilon_{i,t}, \quad (19)$$

where $Q_p(\nabla_{12}y_{i,t}|\cdot)$ is the p^{th} conditional quantile of the annual change⁷⁶ in competition as measured by $y_{i,t}$, which is either the bank-level standard or refined Lerner index; α_p is a constant term; $BankType_{i,t,b}$ is a set of three binary indicator variables ($b = 1, 2, 3$) that take value one if the bank is either a D-SIB (i.e., $b = 1$ for the top seven commercial largest banks), an investment bank (i.e., $b = 2$), or any other non D-SIB (i.e., $b = 3$ includes medium or small-sized niche or specialized deposit-taking institutions).⁷⁷ D_{1t} is a dummy variable that captures the effect of the crisis period that takes value one during 2008:M01 to 2009:M12; D_{2t} is a dummy variable that captures the impact of the post-financial reform period that

⁷⁵To avoid perfect multicollinearity in our model and to simplify the interpretation of our results, we omit the term $\delta_{p,3} \times D_{2t}$.

⁷⁶ $\nabla_{12} = (1 - L^{12})$ is the twelve-month difference operator, and L is the one year lag operator.

⁷⁷In the regression, we exclude the other small banks and treat these institutions as the reference bank type variable.

takes value one during 2014:M01 to 2019:M03; X_t is a set of three macroeconomic control variables (i.e., economic growth, inflation rate, and the twelve-month difference in unemployment rate) that account for business cycle conditions; $Z_{i,t}$ is a set of bank-level controls that account for bank characteristics; $\varepsilon_{i,t}$ is a vector of residuals. To estimate the parameters of a quantile regression, we minimize a weighted sum of absolute errors. It is important to consider that a different associated conditional quantile function is estimated and a different set of weights is assigned to each quantile.

Table 5: Impact of the financial reform at bank level

Variables	Standard Lerner	Refined Lerner
Economic growth _t	-0.1531 (0.1578)	-0.0444 (0.1037)
Inflation rate _t	0.2489 (0.2185)	0.3386*** (0.0930)
∇_{12} Unemployment rate _t	-0.0406 (0.5781)	-0.0665 (0.2974)
∇_{12} Average risk weight _{it}	-0.0669* (0.0381)	-0.0370** (0.0185)
∇_{12} Loan to assets _{it}	0.0460 (0.0610)	0.0644** (0.0297)
∇_{12} Retail funding to liabilities _{it}	0.0299 (0.0413)	0.0131 (0.0176)
∇_{12} Provision to assets _{it}	-1.3334*** (0.4303)	-0.5513* (0.3127)
D_{1t}	-0.0085 (0.0253)	-0.0072 (0.0123)
D_{2t}	-0.0201*** (0.0059)	-0.0023 (0.0029)
α	0.0116 (0.0121)	-0.0135* (0.0069)
Observations	3,902	3,902
R-squared	0.014	0.015
Bank fixed effects	Yes	Yes
Wald-statistic	3.74***	3.87***

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table shows the linear regression estimates can be used to assess any impact on the NEIO measures of competition (i.e., standard and refined Lerner index) stemming from the 2014 financial reform. The model was estimated using a twelve-month difference operator for both dependent variables. We include the R-squared to assess the goodness of fit and the Chi² statistic to test the null hypothesis that all coefficients are equal to zero. The models were estimated using Driscoll and Kraay standard errors (Driscoll and Kraay, 1998).

Linear regression models show the effect of the financial reform at the conditional mean of the bank-level competition measure. In contrast, quantile regression is used to consider the heterogeneity of any bank competition measure when analyzing the effect of the regulatory shock, it and generates multiple coefficients at various points across the conditional compe-

tion distribution.⁷⁸ The three interaction terms show the effect of the financial reform on competition for each bank type separately, which is conditional on the underlying degree of competition per bank type. We also report the traditional regression results to compare how quantiles vary in comparison with conditional mean estimates. The ultimate objective is to assess how the effect of the financial reform on bank type varies across the conditional competition distribution. This analysis provides a multi-dimensional quantitative comparison of the effect of the regulatory reform on the conditional competition intensity (at the bank level) that, to the best of our knowledge, has not been analyzed in previous research. To facilitate the interpretation of our results, we estimate quantile regression for seven percentiles ranging from the 5th to the 95th of the conditional market power distribution. Moreover, we group the three lowest percentiles (i.e., 5th, 10th, and 25th) in the low market power segment, and the three greatest percentiles (i.e., 75th, 90th, and 95th) in the high market power segment. For completeness, we report a generalized F-test to assess whether the null hypothesis that the coefficient estimates on the interaction term between the bank type and the reform variable are equal across all quantiles (e.g., $H_0 : \beta_{05} = \beta_{10} = \beta_{25} = \beta_{50} = \beta_{75} = \beta_{90} = \beta_{95}$) is valid. We also report a pairwise F-test to assess whether the coefficient estimates of the interaction term are equal between any two quantiles (e.g., $H_0 : \beta_{p_s} = \beta_{p_s'}$).

Table 6 shows the results from the quantile regression analysis using the bank-level standard Lerner index as the dependent variable. Column 2 provides coefficient estimates from traditional linear regression analysis. In columns 3 to 9, we present parameter estimates from the quantile regression. We begin by reporting the parameter estimates for the interaction terms; we also report the coefficient estimate for the binary indicator variables. For completeness purposes, we also report the remaining parameters for all macro and micro control variables. Results based on linear regression analysis suggest that only non-D-SIBs were positively affected by the financial reform, as the average market power decreased for this bank group by 0.0188 units. The results based on quantile regression add much more information and detail on how this effect varies by banking group. Table 6 provides subtle or tenuous evidence that the financial reform intensified the market power of D-SIBs in the low market power segment, as one out of the three low segment coefficients is positive and significant at the 5 percent level (i.e., $\delta_{p,2,1}$ for p25). For non D-SIBs, the interaction term is negative

⁷⁸Quantile regression has been used to analyze competition in different contexts, but the evidence is scarce and absent from the literature. Mamatzakis (2015) studies the relationship between structural reforms, bank concentration, profitability, and cost efficiency using quantile regression for a sample of EU banks. Lee (2019) investigates how financial services and governance affect economic growth in the EU using quantile regression. de Ramon et al. (2020) analyze the link between competition and risk using quantile regression.

and statistically significant at the 5 percent level for most cases.⁷⁹ For investment banks, the sign and size of the interaction term leads to mixed findings. On the one hand, we have a positive and significant coefficient for two out of three quantiles ($p05, p10$) in the low market power segment, which suggests that bank competition intensity deteriorated across this bank group. On the other hand, we also have a negative and significant coefficient for all the interaction terms that form a part of the high market power segment, which suggests that bank competition intensity improved across investment banks characterized by large market powers.⁸⁰ Overall, the result seems to be positive in terms of competition given that the effect on the high market power segment persists across all percentiles and the coefficient value in absolute terms is greater compared with those available in the low market power segment. We report that the coefficient estimates for the interaction terms across all quantiles reject the null hypothesis at the 1 percent level. This result provides evidence in favor of the importance of analyzing heterogeneous relationships within banking groups that form a part of the banking sector. Ultimately, this means that the effect of the reform on the banking sector can lead to the improvement or deterioration of competition intensity, depending on the underlying bank type profile-competition profile.

Table A16 in Appendix A reports the results of the quantile regression analysis using the bank-level refined Lerner index as the dependent variable. As in the previous table, column 2 provides coefficient estimates from the traditional linear regression analysis as reference. Overall, except for the specific case of non-DSIBs, the results are very similar in comparison with the previous case. For non-DSIBs, we have mixed findings. The results suggest that competition intensity worsened in two out of three quantiles (i.e., $p05, p10$) that form a part of the low market power segment, while competition intensity improved for all banks that form a part of the high market power segment. Taken together, due to the fact that the median coefficient estimate has a negative sign and is weakly significant at the 10 percent level, we conclude that this result is not qualitatively distinct from the previous standard Lerner case.

⁷⁹The coefficient estimate is positive and significant at the 5 percent level for the first quantile ($p05$) in the low market power segment. We believe that this result is driven by atypical small banks and does not reflect the appropriate sign for this bank group.

⁸⁰The interpretation of the marginal effect is more delicate in the context of quantile regression when assessing the change of a discrete variable. This is because the interpretation assumes that the impact of a unit change in the dummy variable is not strong enough to take the bank out of the quantile under analysis. A large change stemming from a discrete exogenous variable may displace the bank into a different quantile.

Table 6: Quantile regression: using bank-level standard Lerner as dependent variable

Variables	OLS	Low market power segment (High competition)			High market power segment (Low competition)			
	(2)	p05 (3)	p10 (4)	p25 (5)	p50 (6)	p75 (7)	p90 (8)	p95 (9)
<i>Interaction terms</i>								
$D_{2t} \times \text{D-SIBs}_i$	0.0023 (0.0101)	0.0288* (0.0174)	0.0173 (0.0113)	0.0227*** (0.0058)	0.0077 (0.0059)	0.0017 (0.0058)	-0.0249* (0.0148)	-0.0400 (0.0295)
$D_{2t} \times \text{Non D-SIBs}_i$	-0.0188** (0.0089)	0.0426** (0.0180)	-0.0173** (0.0070)	-0.0109** (0.0053)	-0.0123*** (0.0033)	-0.0289*** (0.0071)	-0.0864*** (0.0079)	-0.0912*** (0.0247)
$D_{2t} \times \text{Investment banks}_i$	-0.0182 (0.0353)	0.1322*** (0.0501)	0.0906*** (0.0311)	0.0370 (0.0233)	-0.0036 (0.0136)	-0.0585*** (0.0208)	-0.1300*** (0.0472)	-0.2207*** (0.0475)
<i>Bank group binary indicators</i>								
D-SIBs _i	-0.0126 (0.0386)	0.2465*** (0.0463)	0.1979*** (0.0269)	0.0720*** (0.0202)	-0.0195 (0.0125)	-0.1345*** (0.0218)	-0.2006*** (0.0469)	-0.2886*** (0.0545)
Non D-SIBs _i	0.0047 (0.0377)	0.2033*** (0.0485)	0.2079*** (0.0253)	0.0949*** (0.0188)	0.0004 (0.0125)	-0.1024*** (0.0220)	-0.1305*** (0.0436)	-0.2012*** (0.0529)
<i>Macroeconomic and global crisis controls</i>								
Economic growth _t	-0.2038 (0.1662)	0.2503 (0.3720)	-0.2076 (0.1875)	-0.0513 (0.1274)	0.3008*** (0.1074)	0.4331** (0.1890)	0.0365 (0.2996)	-0.7162 (0.7404)
Inflation rate _t	0.2120 (0.1756)	0.4233 (0.5399)	0.0683 (0.3771)	0.2060 (0.1618)	0.1606 (0.1193)	0.0727 (0.1365)	0.1156 (0.2544)	-0.0435 (0.5822)
$\nabla_{12} \text{Unemployment}_t$	0.0853 (0.6280)	0.6100 (1.1479)	0.2916 (0.9791)	0.1694 (0.4646)	-0.1472 (0.3143)	-0.3814 (0.4637)	0.5713 (0.9857)	5.3243*** (1.7521)
D_{1t}	-0.0166 (0.0255)	0.0344 (0.0365)	-0.0305 (0.0188)	-0.0346*** (0.0125)	-0.0170** (0.0077)	0.0076 (0.0234)	-0.0008 (0.0309)	-0.0841* (0.0487)
<i>Bank-level controls</i>								
$\nabla_{12} \text{Average risk weight}_{i,t}$	-0.0868* (0.0440)	-0.1736*** (0.0371)	-0.1434*** (0.0391)	-0.0569** (0.0233)	-0.0744*** (0.0190)	-0.0964*** (0.0147)	-0.0619** (0.0248)	-0.1134*** (0.0348)
$\nabla_{12} \text{Loan to assets ratio}_{i,t}$	0.0255 (0.0597)	0.1969** (0.0841)	0.1079 (0.0715)	0.0734 (0.0451)	0.0582* (0.0308)	0.0931** (0.0390)	0.0564 (0.0457)	0.0221 (0.0991)
$\nabla_{12} \text{Retail funding to liabilities ratio}_{i,t}$	0.0488 (0.0338)	-0.0039 (0.0548)	0.0124 (0.0318)	0.0414* (0.0219)	0.0173 (0.0198)	0.0434* (0.0247)	0.2159*** (0.0235)	0.3188*** (0.0405)
$\nabla_{12} \text{Provision ratio}_{i,t}$	-0.7822** (0.3508)	-0.7366 (0.7416)	-1.3770** (0.6724)	-1.4179*** (0.4697)	-0.8228*** (0.2321)	-0.7681*** (0.2380)	-0.1681 (0.2827)	0.7523 (0.4876)
α	0.0111 (0.0339)	-0.3972*** (0.0613)	-0.2771*** (0.0318)	-0.1263*** (0.0196)	0.0014 (0.0121)	0.1525*** (0.0227)	0.2855*** (0.0501)	0.4659*** (0.0424)
$R^2/\text{Pseudo } R^2$	0.015	0.11	0.08	0.03	0.02	0.05	0.1	0.13
F-test of equality of coefficient on interaction term across all quantiles								
F-test $D_{2t} \times \text{D-SIBs}$		4.47***						
F-test $D_{2t} \times \text{Non D-SIBs}$		36.51***						
F-test $D_{2t} \times \text{Investment banks}$		6.19***						

Table 6. (Continued)

Variables	OLS	Low market power segment (High competition)				High market power segment (Low competition)		
	(2)	p05 (3)	p10 (4)	p25 (5)	p50 (6)	p75 (7)	p90 (8)	p95 (9)
F-test of pairwise equality of coefficients estimates on $D_{2t} \times$ D-SIBs between quantiles								
p05			0.54	0.11	1.22	1.93	6.26**	5.61**
p10				0.75	1.57	2.86*	8.35***	7.69***
p25					9.48***	4.64**	7.62***	8.86***
p50						0.68	4.06**	5.98**
p75							5.33**	4.99**
p90								0.92
F-test of pairwise equality of coefficients estimates on $D_{2t} \times$ Non D-SIBs between quantiles								
p05			10.84***	6.86***	5.77**	9.21***	20.24***	13.84***
p10				1.04	0.32	1.38	17.85***	7.13***
p25					0.08	9.04***	32.85***	10.85***
p50						12.33***	37.55***	11.74***
p75							37.51***	8.79***
p90								0.08
F-test of pairwise equality of coefficients estimates on $D_{2t} \times$ Investment banks between quantiles								
p05			0.85	4.20**	5.79**	9.56***	16.05***	16.16***
p10				6.93***	19.76***	25.29***	23.99***	28.21***
p25					3.22*	12.34***	13.10***	17.31***
p50						9.97***	14.76***	19.99***
p75							3.64*	11.11***
p90								3.64*

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level. This table displays the linear and quantile regression results. The dependent variable in all specifications is the standard Lerner index at the bank level. The conditional mean and quantile regression estimations use all banks in the sample and monthly data between 2008:M01 and 2019:M03. Column (2) shows the estimation using ordinary least squares. Columns (3) to (9) report the quantile regression estimates. We report the traditional R^2 in ordinary regression, while pseudo R^2 are generated for the quantile regression. The F-statistic is used to reject the equality of coefficients on the interaction term across all quantiles as well as between any two quantiles. The interaction terms measure the joint effect of the financial reform (D_{2t}) for the following: (i) D-SIBs; (ii) other small banks; (iii) investment banks. We include common macroeconomic controls and bank-level controls based on the literature. All continuous variables are measured using annual changes. All quantile regression specifications are estimated using STATA's command "sqreg" with bootstrap standard errors. The number of replications used to obtain the estimate of the variance-covariance matrix of the estimators (standard errors) is 20. All in all, we use 3,902 observations in the estimations.

Figure 6 shows the effect of the financial reform per bank type for varying quantiles of the market power measure based on the standard Lerner index. It shows that quantile coefficients on all three interaction terms alternate signs. All coefficients begin with a positive sign at low quantile levels and finish with a negative sign at high quantile levels. However, coefficient estimates are not statistically significant for all quantile levels. Panel A in Figure 6 shows that for D-SIBs, only one of the seven analyzed quantiles is statistically significant and positive at the 5 percent level (i.e., p_{25}). Panel B in Figure 6 shows that for investment banks, we have significant coefficients at the 5 percent level with a number of coefficients that have both positive (i.e., p_{05} , p_{10}) and negative (i.e., p_{75} , p_{90} , p_{95}) values. Panel C in Figure 6 shows that for non-DSIBs, except for the first quantile (p_{05}), which is positive and significant, all remaining interaction coefficients are negative and significant at the 5 percent level. Moreover, the size of the impact in the first (i.e., p_{05}) and last (i.e., p_{95}) quantile decreases significantly as we move toward the median. This result may be the result of data scarcity in both the lower and upper tails of the market power distribution, and it implies that prudence should be exercised when analyzing the coefficient point estimates of these quantiles.

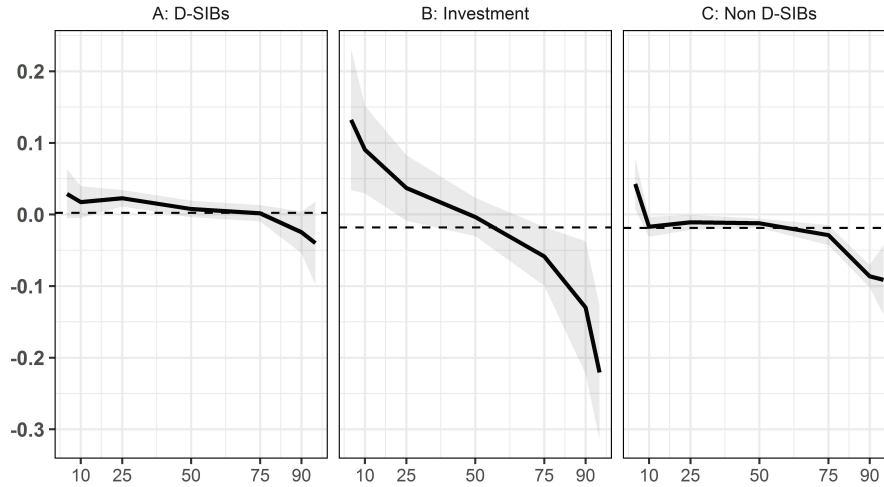
Figure 6 also shows that the conditional mean estimate that represents the average effect of the financial reform per bank type (depicted by the dashed line) does not vary with the quantile level and is statistically different across a broad range of market power percentiles. For completeness purposes, Figure A22 in Appendix A shows the effect of the financial reform per bank type for varying quantiles of the market power measure based on the refined Lerner index. Findings are qualitatively similar to the previous case.

All in all, these findings imply that the effect of the financial reform on competition has a varying intensity per bank type. This may have different effects on bank behavior and may influence bank's risk taking activities in a way that deserves further study. This result is relevant, as there may be trade-offs to consider, especially when designing policies for stimulating competition in the banking sector. To the best of our knowledge, this result has not been documented in previous empirical research studies that investigate the evolution of competition.

5.1.5.4 Time Series Markov Switching Model to Identify Changes in Regime

Markov switching models provide a time series framework that allows any variable to follow a different process over sub-samples. A Markov chain is a useful tool to generate a process that adopts changes in regime. This framework is adequate for any of the following cases:

Figure 6: Marginal effect of the financial reform per bank type on quantiles of the standard Lerner index



Source: Banco de México, authors' calculations

Notes: Each panel shows the value of the estimated interaction coefficients per bank type (vertical axis) for varying quantiles of the market power measure based on the standard Lerner index (horizontal axis). The solid line shows the transition of the estimate of the interaction terms' coefficients, while the shaded area represents the 95% confidence interval using bootstrap standard errors. The dotted line represents the conditional mean estimate (OLS estimation) of the interaction term, and this line is independent of the quantiles of the market power.

(i) the underlying mechanism driving the change is thought of as permanent; (ii) there is an interest to obtain a meaningful forecast prior to the change to account for the probability of a change from state 1 to state 2; (iii) there is a need for a time series model that accounts for short-lived events. The main objective of this analysis is to identify endogenously different competition regimes as well as their transition probabilities. This information is useful for assessing how persistent can each state be. Moreover, we also wish to determine whether an intense competition state is more likely to happen as a consequence of the 2014 financial reform.

We estimate a simple dynamic Markov switching model (see Hamilton and Press (1994)) with two regimes: one associated with an increase in competition intensity (i.e., $s_t = 1$) and the other with a decrease in competition intensity (i.e., $s_t = 2$). In this setting, s_t is unobservable, but we assume that it follows a Markov chain. The discrete latent state s_t determines the evolution of the competition regime and has a transition matrix where the entry i, j is defined as the probability that state j will happen given that we are currently in state i (see Hamilton and Press (1994)). This model is estimated by maximum likelihood. To be consistent with the previous section, we use the twelve-month difference operator for our competition measures.

The model specification is defined as follows:

$$\nabla_{12}y_{it} = \alpha_{s_t} + \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0, \sigma_{s_t}^2), \quad (20)$$

where $\nabla_{12} = (1 - L^{12})$ is the twelve-month difference operator (L is the lag operator) that uses either the aggregate mean or median of (i) the standard or (ii) refined Lerner index or (iii) the Boone indicator as the dependent variable (y_{it}); α_{s_t} is the conditional mean at state s_t ; σ_{s_t} is the conditional standard deviation at state s_t .

Table 7 shows the estimates for the Markov switching regime change. We find evidence of two persistent and significant regimes for bank competition. Specifically, α_1 and α_2 are the conditional mean of the endogenous variable in state 1 and state 2, respectively. As expected, the conditional mean is lower (i.e., high competition intensity) in state 1. Additionally, the conditional standard deviation in state 1 (i.e., high competition intensity) is lower than that in state 2 only for the standard Lerner index and the Boone indicator. We also show the transition probability from state 1 to remain in state 1 (i.e., $p_{1,1}$) and the transition probability from state 2 to state 1 (i.e., $p_{2,1}$)⁸¹. Given that $p_{1,1}$ and $p_{2,2}$ are greater than 0.85 for all competition measures, we conclude that both competition states are highly persistent. This means that once the process enters any of these two states, it will remain there for a number of periods.

Figure 7 shows the evolution of each competition measure using the twelve-month annual variation (i.e., dark blue solid line), while the red dashed line (plotted in the right hand axis) shows the probability of being in a high competition regime. Additionally, we include the estimated conditional means of each regime (green dot lines) where the bottom green line denotes the conditional mean in the state of increasing competition. Panel A shows the evolution for the annual variation of the mean of the standard Lerner index. We identify three periods of intense competition, and these are highlighted in red (i.e., the first during 2009 to 2010, the second during 2014-2016, and the last during 2017 to 2019). Panel B shows the evolution for the annual variation of the median of the standard Lerner index. We identify five periods of intense competition (i.e., first during 2009 to 2010, the second during 2014-2016, and then three more, one in each of the following years: 2016, 2017, and during 2018 to 2019). Panels C and D show the evolution for the annual variation of the mean and median of the refined Lerner index, respectively. There is evidence of at least four periods

⁸¹It is simple to compute the probability of transition from state 2 to state 2 as $p_{2,2} = 1 - p_{2,1}$

Table 7: Markov switching regime specifications

Variables	Lerner standard		Lerner refined		Boone
	Mean	Median	Mean	Median	
α_1	-0.0155*** (0.0017)	-0.0098*** (0.0031)	-0.0109*** (0.0013)	-0.0081*** (0.0012)	-0.0364*** (0.0051)
α_2	0.0181*** (0.0018)	0.0203*** (0.0029)	0.0051** (0.0008)	0.0079*** (0.0014)	0.0181*** (0.0039)
σ_1	0.0088*** (0.0011)	0.0088*** (0.0023)	0.0058*** (0.0006)	0.0064*** (0.0006)	0.0128*** (0.0037)
σ_2	0.0133*** (0.0014)	0.0124*** (0.0011)	0.0052*** (0.0004)	0.0047*** (0.0007)	0.0211*** (0.0018)
$p_{1,1}$	0.9510*** (0.0270)	0.9264*** (0.0531)	0.9191*** (0.0277)	0.9470*** (0.0201)	0.9120*** (0.0420)
$p_{2,1}$	0.0380*** (0.0173)	0.0731*** (0.0266)	0.0379*** (0.0185)	0.0879*** (0.0300)	0.0688*** (0.0273)
Obs	121	121	121	121	111

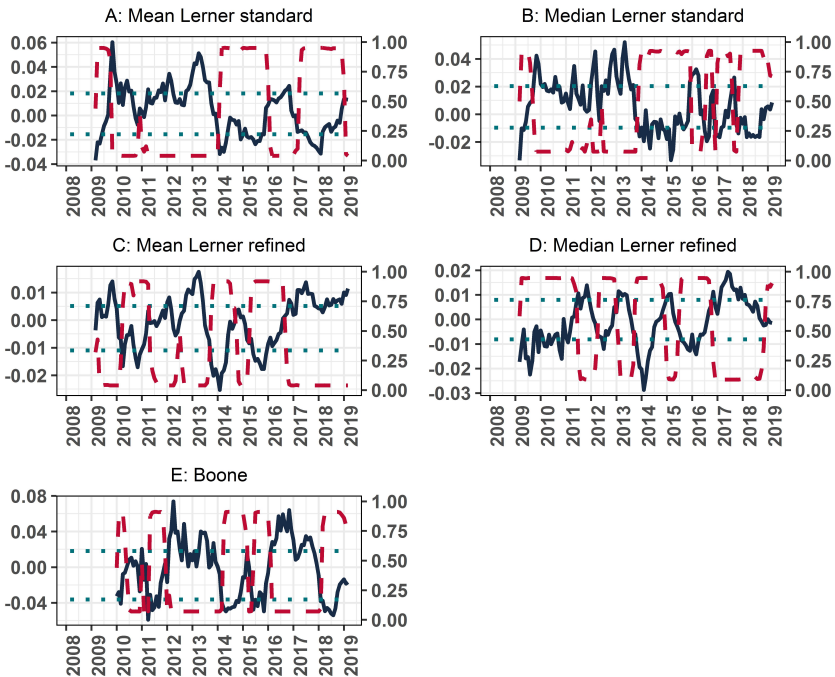
Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the Markov switching model estimates for the competition measures. All estimations were done in Stata using the command 'mswitch', which is used for Markov regime switching estimations. All the estimations are based on eq.(20). All the specifications were estimated using robust standard errors.

of intense competition regimes for the mean of the Lerner refined (i.e., first a brief period at the beginning of 2009, the second during 2010-2011, the third during 2014-2015, and the last during 2015-2017). For the median of the refined Lerner index, we find evidence of five periods of intense competition regimes (i.e., first from 2009 to 2011, the second from 2012 to 2013, a third from mid-2013 to 2015, the fourth from 2015 to 2017, and the last from the end of 2018 to 2019). Finally, the Boone indicator signals five competition regimes (i.e., first a brief period during 2010, the second in 2011, the third from 2014 to early 2015, the fourth from 2015 to end-2016, and the last from 2018 to 2019). Overall, all the analyzed NEIO competition measures suggest that there was a period of intense competition starting in 2014. This result provides evidence supporting the view that the 2014 financial reform intensified competition pressures. Nonetheless, the evidence provided by the refined Lerner index and the Boone indicator is weaker compared with that provided by the standard Lerner index.

Additionally, in Appendix A, we present a Markov switching model using the composite competition indices based on principal components analysis. All in all, the composite competition indices suggest that there is a period of intense competition starting in 2014. This result provides evidence supporting the view that the 2014 financial reform intensified competition pressures. In addition, the information content of both composite indicators is less noisy in comparison with the individual competition measures used to construct them.

Figure 7: Markov switching model for a twelve-month difference in the competition measures



Source: Banco de México, authors' calculations
Notes: This figure shows the evolution of the twelve-month difference of each competition measure (dark blue solid line), the conditional means of each competition regime (green dot line), and the probability of a high competition regime (red dashed line). Panels A and B show the mean and median of the standard Lerner index, respectively. Panels C and D show the mean and median of the refined Lerner index, respectively. Panel E shows the Boone indicator. The left vertical axis measures the value of the twelve month difference in the competition measure. The right vertical axis measures the probability of a high or intense competition regime. The labels on the horizontal axis indicate the end of the year.

6 Conclusions

This paper examined the evolution of competition in the Mexican banking sector using popular TIO and NEIO indicators. In particular, we analyzed if the trends among competition measures follow a similar or consistent pattern in terms of competition intensity. Moreover, we investigated how the distribution of some of our measures evolved to assess changes in competition intensity during our sample period. Specifically, we assessed if there was any distributional change following the financial reform that took effect in 2014, and we controlled for any potential effect linked to the global financial crisis period. To the best of our knowledge, this is the first study of its kind that incorporates almost all banks for a single country using monthly information that analyzes the average and heterogeneous effects of a regulatory shock and its duration.

We found that the evolution of competition indicators at the bank-level is heterogeneous. Specifically, according to the standard Lerner index, D-SIBs have, on average, benefited from an increase in their market power throughout the period. The evidence is not so strong according to the refined Lerner index, as D-SIBs have, on average, benefited from an increase in their market power until mid-2015. We reported a different path for the trend followed by the overall competition intensity between the unweighted standard and the unweighted refined Lerner index. Specifically, according to the standard Lerner index, competition intensity deteriorated from end-2008 to mid-2013, and then it remained stable. In contrast, according to the refined Lerner index, competition intensity improved (albeit with a certain degree of volatility in a few time periods) from early 2008 to 2016 and, then, it slightly worsened.

Regarding TIO competition measures, we found that the number of banks increased steadily during our sample period, and concentration decreased. In our sample, there were only two bank mergers, and these did not raise concern among regulators. However, the market share of medium and small banks remained very small, and the reduction in concentration was marginal, as its level is relatively high. Moreover, it is well documented in the literature that TIO measures are not a good proxy for competition.

A noteworthy novelty of this paper is that we developed monthly competition indicators. We performed robustness test using quarterly estimates to verify that our estimates were consistent. This is a useful contribution. Policymakers will benefit from this approach, as it allows more frequent monitoring of competition intensity and its evolution. Researchers will benefit from this approach, as this frequency is more adequate to capture any shock type. Moreover, in future research, it will be possible to test the relationship either between competition and bank risk taking or between competition and pricing at the bank level with a more granular and finer sample.

In relation to the evolution of competition intensity and the impact of the global financial crisis of 2008, our traditional regression analysis at the aggregate and bank level suggested that it had no effect. In contrast, our assessment on the impact of the financial reform led to mixed results. On the one hand, our regression analysis at the aggregate level showed that only three out of four individual NEIO competition measures, i.e., standard Lerner index (mean and median), Boone indicator, and composite index, suggested that there is, on average, a positive and significant effect that increases competition intensity. Moreover, our regression analysis at the bank level supported the view that there is evidence of a positive impact only in the case of the standard Lerner index. On the other hand, our quantile regression analysis at

the bank level showed that the effect of the financial reform was heterogeneous across bank types. There is strong evidence of the fact that competition across non-DSIBs intensified, while there is tenuous or subtle evidence that it deteriorated across D-SIBs. Moreover, we found that competition across investment has mixed results, as banks in the low (high) market power segment experienced a decrease (increase) in terms of competition intensity.

To complement the traditional regression analysis, we estimated a two-regime⁸² Markov switching model on both Lerner indices and the Boone indicator. We found evidence only with the Lerner indices that in the case of the global financial crisis, there was a positive impact on competition intensity starting in 2009. It is unclear why the effect was not picked up starting 2008. In contrast, regarding the financial reform, we found that all the analyzed NEIO competition measures at the individual level showed evidence that there was a period of intense competition starting in 2014. Additionally, this result was supported by the composite bank competition index. Notwithstanding this, it is not clear why there is high heterogeneity in the duration of the intense competition state. For example, according to the mean and median of the standard Lerner index and the composite bank competition index, competition remained intense at least for two years after 2014 and then also after a brief period during 2016-2017 of less competition. In contrast, the mean and median of the refined Lerner index and the Boone indicator suggested that competition remained intense only during a one-year period. Overall, in the long term, we did not find evidence of a lasting positive impact on competition for the refined Lerner index. These results led us to conclude that there is partial, albeit robust, empirical evidence supporting the fact that the financial reform intensified competition in the Mexican banking sector. However, there is no evidence that the regulatory changes in isolation have helped to reduce the dominant market power of D-SIBs.

In this study, we analyzed the effect of the financial reform conceived as a package that incorporates a number of individual policy measures. In other words, we analyzed the simultaneous joint effect of several different measures. Our study offers a partial view, as we did not analyze the effect of individual policy measures. Our main recommendation is that other competition measures at the individual product level should be considered to assess how adequate the individual policy measures implemented in the 2014 financial reform have been. Additionally, more research studies based on quantitative indicators are required to shed light on the progress and the required steps forward. It would also be convenient to develop more theoretical models and metrics to enhance the monitoring of competition among banks and

⁸²Each regime is associated with either an increase or a decrease in competition intensity.

non-bank entities as well as to reduce market failures in the banking sector.

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Appendix A: Supplementary Statistical Analysis

In this section, we provide empirical statistical analysis that serves as a reference or as a supplement to our paper. We have structured this section as a collection of sub-items that appear in chronological order (i.e. Table or Figure) as reported in the paper. We believe that the information content is either too broad, too detailed or not strictly relevant to be included in the main manuscript of this study.

A.1 Background on SOFOLES and SOFOMES

SOFOLES were created in 1994 and were regulated and supervised financial intermediaries that focused on niche lending activities. SOFOLES do not have access to stable funding such as deposits. SOFOLES's loan business model was funded mainly by banks' short term funds, while large SOFOLES were also able to issue debt in capital markets. In 2006, a new regulatory framework allowed SOFOLES that were not affiliated to any bank (i.e., or financial group) or those that did not issued public debt to operate as unregulated and therefore unsupervised entities. The entities that adopted this new framework converted/transformed into Multiple Purpose Financial Societies (i.e., SOFOMES, its acronym in Spanish). Wide mistrust and fund withdrawal led to the demise of this industry. Only a few SOFOLES made it through the financial crisis as most of them merged with financial groups.

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. There are two types of SOFOMES: regulated and unregulated. Compared to banks, a regulated SOFOME offers tax benefit to its shareholders. Thus, banks usually transfer some of its business lines (i.e., credit cards) and originate a subsidiary entity as a SOFOME to manage it. Alternatively, any SOFOME that issues debt in the stock market has also to be regulated even if it is not a bank subsidiary. In contrast to banks, SOFOMES are not allowed by law to raise funds from public deposits. This is the reason why SOFOMES are also known as “non-deposit-taking and non-specialized loan institutions”.

A.2 Data: Variable Definitions

Table A1 presents the definition of the variables used in our paper.

A.3 Traditional Industrial Organization (TIO) or Concentration Measures

In any industry, the number of firms is a time varying variable that captures the evolution of the number of firms that either enter or exit due to competition intensity or regulatory factors. However, this is not a strong measure to assess the level of concentration in the banking industry because the size and efficiency of each bank are not taken into account.

Since any financial industry may be largely dominated by one bank or by a group of relatively large banks, researchers have used the k -bank concentration ratio. For any point in time t , this ratio measures the market share on any variable of the top K banks in the industry:

$$CR_{k,t} = \sum_{i=1}^K s_{i,t}, \quad (21)$$

where $s_{1,t} \geq \dots \geq s_{K,t} \geq s_{N,t}$, $\forall N \geq K$, $s_{i,t}$ is the market share of the i -th bank at time t , where banks are ranked in descending order of market share and N is the total number of banks. The index tends to 1 when a single firm owns the entire industry and it approaches zero as the number of equally sized banks included tends to infinite. In practice, there is no rule to determine the optimal value of K and a large majority of studies consider a set of three or more values such as 3, 5, 10. In Mexico, banks can be grouped into two types: (i) domestic systemically important banks (D-SIBs) (i.e., the seven largest banks identified as D-SIBs) and (ii) non-D-SIBs (i.e., small banks). In this paper, we use $K=7$ as a CR value to assess the degree of concentration held by D-SIBs⁸³. Moreover, we compute $CR_{7,t}$ based on the

⁸³See Basel Committee on Banking Supervision (BCBS) (2012) for a list of principles and a framework for national authorities to identify and deal with D-SIBs. Following BCBS (2012), CNBV identified and labelled seven banks (i.e., BBVA Bancomer, Citibanamex, Banorte, Santander, HSBC, Scotiabank and Inbursa) as D-SIBs starting May 2016. Each year, the Financial Stability Board publishes a list of global systemically important banks (G-SIBs). According to FSB (2019) three Mexican D-SIBs (i.e., Citibanamex, HSBC, Santander) are also foreign subsidiaries of global systemically important banks (G-SIBs). The G-SIB list published by FSB varies each year since 2014, and due to its varying nature, we believe that a concentration measure based on D-SIB criterion is more accurate and representative of the Mexican banking sector structure.

share of each bank total assets, total loans and total deposits in the banking sector. A high market share is associated with a high level of market power. Nevertheless, this measure fails to take into account the size distribution of remaining banks and it does not satisfy all the key desirable criteria met by a good concentration index as suggested by Hall and Tideman (1967).

The Herfindahl-Hirschman Index collects information on the entire bank size distribution and it meets all minimum desirable criteria introduced by Hall and Tideman (1967). Thus, this measure can be regarded as a good indicator of market concentration. For any point in time t , the HHI is computed by summing the square of the market share of each bank as:

$$HHI_t = \sum_{i=1}^N s_{i,t}^2, \quad (22)$$

where $s_{i,t}$ is the share of bank i at time t and N is the total number of banks in the financial system. The index can take any value close to zero (i.e., a large number of equally small sized banks) and up to 10,000 (i.e., a single bank has the monopoly of the entire industry). Thus, a higher HHI value signals a more concentrated market. The Mexican competition authorities use the HHI as an early warning indicator to assess any competition issue worth investigating and also to determine whether any merger represents a threat to competition within any industry. In particular, if the HHI is greater than 2,000, then COFECE considers the market is concentrated and investigates it.⁸⁴ Broadly, any horizontal merger that increases the HHI by more than 100 represents a source of concern for COFECE.⁸⁵ In our sample, we have a few mergers and this threshold value may be a useful reference. In this study, to assess the evolution of concentration, we calculate three types of HHI based on the size of each bank's: loan portfolio, total assets and total deposits held. Concentration measures have low data requirements and information to compute them is available for almost all countries (see Demsetz (1973), Berger (1995), Leon (2015b)). However, concentration and competition measures are two different concepts that may not be related (see Leon (2015b) for details).

⁸⁴See rules text available at http://www.dof.gob.mx/nota_detalle.php?codigo=5392185&fecha=14/05/2015; accessed on July 17, 2020. Threshold values for HHI vary across jurisdictions. The U.S. Department of Justice (see U.S. Department of Justice & FTC (2010)) applies a stricter criteria and requires a HHI value to be greater than 2,500 to define a market as highly concentrated, while the UK competition authorities request a HHI value of at least 1,000 (see Commission et al. (2014)). Interestingly, to the best of our knowledge, threshold values do not vary across industries and this means that market structure between financial and non-financial industries is assumed to be similar.

⁸⁵See rules text available at http://www.dof.gob.mx/nota_detalle.php?codigo=5392185&fecha=14/05/2015; accessed on July 17, 2020.

Broadly, concentration measures reflect only aggregate information of the market structure, but this fails to inform about each bank conduct and its business strategy which remains uncertain. Specifically, concentration measures design is limited as it fails to provide individual bank-level variables.

Figure A2 shows how the number of bank entities evolved in our sample. There is a consistent upward trend where the number of banks increased from 27 in 2007 to 40 in mid-2016. There are two points in time where the number of banks decreased. The first occurs in April 2012 (i.e., Banorte merged with IXE) and the second in July 2018 (i.e., Banorte merged with Interacciones), and both are characterised as a merger between a D-SIB and a non-D-SIB bank that did not raise any issue in terms of competition.⁸⁶ It is convenient to point out that all banks that have entered the Mexican market during this period are non-DSIBs. Figure A3 shows the concentration ratio for the seven D-SIBs (i.e., CR_7), for the following three balance sheet items: total assets, total private non-financial loan portfolio and total deposits. There is a downward trend for all three measures that suggests that concentration is improving, but at a very slow rate during the sample period. The CR_7 measured by total assets shows a slight increase during the financial crisis and then it displays a steep decline in the aftermath and oscillates from 2012 around 78%. In contrast, the CR_7 measured either by loan portfolio or total deposits shows a smooth downward trend with very similar levels for both measures. Interestingly, the three CR_7 show a small spike in July 2018 that can be attributed to the bank merger between Banorte and Interacciones. Although there is slight improvement in terms of less concentration, the Mexican banking sector is largely concentrated in seven D-SIBs.⁸⁷ Five out of the seven D-SIBs are foreign bank subsidiaries, while Banorte and Inbursa are the only two D-SIBs that are under the control of Mexican shareholders. Figure A4 shows the HHI indices for the following three balance sheet items: total assets, total private non-financial loans and total deposits. There is a downward trend for all three measures that suggests that concentration is decreasing during the sample period. This is because both medium and small size banks increased their market share. Before the financial crisis took

⁸⁶Overall 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 that took place in July 2018 was not taken into account and we did not create a new entity. However, we took out both entities from our analysis. This is due to data constraints as we do not have a window of at least 12 months, which is required to compute some of our variables.

⁸⁷Figure A1 shows the bank's market share grouped by type of business model using total assets, total private non-financial loan portfolio and total deposits. It can be seen that the market share of D-SIBs has decreased during our time period, while the market share of Mid-Size and specialized banks has increased. The difference in terms of market share between D-SIBs and non-D-SIBs is large independently of the variable under analysis (i.e. total assets, total private non-financial loan portfolio and total deposits).

place, our data shows that both total assets and deposits were concentrated in few large banks. Interestingly, the *HHI* for total assets increased in the aftermath of the financial crisis and started to decline steeply in 2010 and this continued up to mid-2018. Given that there is no spike in the evolution of the *HHI*, we can conclude that none of the bank mergers that took place during this period can be considered as large. The level of the three *HHI* is lower than 2,000, and broadly, according to Mexican standards, this means that there is no source of concern for Mexican competition authorities as the banking industry is not concentrated.⁸⁸ According to the *HHI*, the Mexican financial reform introduced in January 2014 did not accelerate the downward trend and there is no sign that new competition incentives reduced significantly the level of concentration in this industry. However, the analysis and conclusions from this competition measure are limited to the banking industry as the role of non-bank financial intermediaries in traditional loan markets is not taken into account. Moreover, there is no sign of impact from a significant new entry into the banking market between 2007 and 2019. Finally, the three *HHI* increase slightly in July 2018 with the merger between Banorte and Interacciones.

A.4 Competition Measures: Standard Lerner Index

Following our robustness test, Table A2 shows the five estimated translog cost function used to compute the standard Lerner index as described in section 4.2.1.1 using eq.(2). Specifically, the cost function has been estimated for the following five models: (i) time and bank fixed effects⁸⁹ with clustered standard errors grouped by individual banks (i.e. baseline case, M1); (ii) exclude time and bank fixed effects with clustered standard errors grouped by individual banks to assess the impact of neglecting heterogeneity (i.e. M2); (iii) bank type to control for heterogeneity across banks' business models with clustered standard errors grouped by individual banks (i.e. M3); (iv) time and bank fixed effects without clustered standard errors grouped by individual banks to assess if there is any statistical significance impact when neglecting robust standard errors techniques (i.e. M4); and (v) bank fixed ef-

⁸⁸The level of the *HHI* is high according to competition standards in other jurisdictions such as in the UK where any *HHI* greater than 1,000 is considered as concentrated and potentially worth of investigation (Commission et al. (2014). Mexican authorities should revise if a generalized threshold of 2,000 is adequate for all industries.

⁸⁹Time fixed effects were introduced to control for heterogeneity for each month and for business cycle conditions. Bank type fixed effects were introduced to take into account heterogeneity across four different bank business models.

fects with macroeconomic control variables and time fixed effects with clustered standard errors grouped by individual banks (i.e. M5).

Figure A5 shows the evolution of the unweighted average of the standard Lerner index of the banking sector for different specifications (i.e. M1, M2, M3 and M5). We do not show M4 as this model is the same as M1 and the only difference between them is the method to compute the parameters standard errors which has no impact on the Lerner point estimate. Panel A is our baseline model. Panel B is M2, excluding time and bank fixed effects leads to a lower Lerner index level, while the pattern remains broadly the same. Panel C controls for bank's type. Unfortunately, the level of the standard Lerner index remains relatively low to the values reported in the literature. Panel D shows that the inclusion of macro control variables does not modify the level or pattern or trend of the standard Lerner index. Due to its simplicity and the fact that the reported values are similar to those available in the literature, our preferred choice is our baseline model M1.

Figure A6 to A8 show the evolution of the weighted (i.e. by total assets, size of private non-financial loan portfolio and total deposits) and unweighted standard Lerner index of the Mexican banking sector.

A.5 Competition Measures: Refined Lerner Index

Following our robustness test, Table A3 contains the five estimated stochastic frontier cost function used to compute the refined Lerner index as described in section 4.2.1.2 using (11). Specifically, model M1 is the baseline which includes fixed effects by individual bank to account for heterogeneity. Model M2 is estimated with a pooled approach (i.e. excluding bank fixed effects). Model M3 is M1 with macroeconomic controls. Model M4 is M3 with bank-level control variables. Model M5 is the same as our baseline (i.e. M1) excluding clustered standard errors grouped by bank. Except for model M5, all remaining models were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks.

Figure A9 to A11 show the evolution of the weighted (i.e. by total assets, size of private non-financial loan portfolio and total deposits) and unweighted refined Lerner index of the Mexican banking sector.

Figure A12 shows the evolution for the refined Lerner index for different specifications (i.e. M1, M2, M3, and M4). Each specification is fully described in Table A3. We do not show M5 as this model is the same as M1 and the only difference between them is the method to compute the parameters standard errors which has no impact on the Lerner point estimate.

A.6 Competition Measures: Panzar-Rosse H Statistic

The Panzar-Rosse H -statistic (see Panzar and Rosse (1987)) is a widely used static competition measure that captures the transmission of input prices (i.e., labor, physical capital and deposits) on banks' revenues. This is a proxy for market power in any industry that reflects banks competitive behaviour with respect to input prices and costs (de Ramon and Straughan, 2019). The H -statistic is defined and estimated from a reduced-form revenue model as the sum of banks input price elasticities.⁹⁰ If the value of this indicator is between zero (i.e., no pass-through of costs to revenue) and one (i.e., full pass-through of costs to revenue) it is evidence of monopolistic competition; if the H -statistic is negative or zero it is evidence of neoclassical monopoly or collusive oligopoly and if the value is equal to 1, there is evidence the market behaves as perfect competition (see Panzar and Rosse (1987), Claessens (2009)). Note however that since the H -Statistic is not necessarily a monotonic function of the degree of market competition for all market structures, then a smaller value of H does not necessarily imply greater market power (see Panzar and Rosse, 1987, Shaffer, 1983, Bikker et al., 2012).

To estimate the Panzar-Rosse H -statistic we follow Bikker et al. (2012) and estimate a unscaled reduced-form revenue equation⁹¹ relating gross revenues to a vector of input prices and other firm-specific factors and control variables in order to take into account additional information and proxies about costs, market equilibrium and market demand elasticities. The reason for doing this is that Bikker et al. (2012) shows that the appropriate H -statistic based on an unscaled revenue equation requires additional information about cost and market structures to correctly infer the degree of competition. The reduced form revenue equation is defined as:

$$\log(TR_{it}) = \alpha_i + \eta_t + \sum_{k=1}^3 \gamma_k \log(W_{it}^{(k)}) + \delta X_{it} + \varepsilon_{it}, \quad (23)$$

⁹⁰Panzar and Rosse (1987) show that the overall level of competition in an industry can be inferred from the sum of input prices elasticities. This model assumes linear homogeneity of marginal costs in factor prices.

⁹¹Bikker et al. (2012) show that a proper revenue equation must exclude any scaled variable such as the ratio of revenue to total assets as dependent variable. This caveat is important because there are many empirical applications that use a scaled variable and these studies should have been revised.

where TR_{it} is the bank's i total revenues at time t , α_i and η_t are bank and time fixed effects, $W_{it}^{(k)}$ are three input prices for interest, labor and operational costs which are approximated as the ratios of interest, labor and operational expense to total assets, X_{it} are a set of control variables that reflect banks behavior and risk profile.⁹² The previous equation is estimated using a panel fixed effects estimator with bank and time fixed effects that considers clustered standard errors to allow for bank intragroup effects. After we have estimated eq.(23), the H -statistic can be calculated as:

$$H = \sum_{k=1}^3 \gamma_k, \quad (24)$$

where γ_k are the three input price elasticities estimated from eq.(23).

It is important to highlight that a negative H value may arise under various conditions and even competitive markets can exhibit negative H values if the market is in structural disequilibrium. To test if the market is in structural or long-term equilibrium we follow Shaffer (1982), Bikker et al. (2012), de Ramon and Straughan (2019) and estimate eq.(23) using return on assets (ROA) of each bank instead of logarithm of total revenues⁹³. The rationale behind this test is that in a free entry equilibrium among homogeneous firms, the market should equalize ROA across firms, so that it is independent of input prices (see Bikker et al. (2012)). Shaffer and Spierdijk (2015) studies five alternative oligopoly settings and shows that the sign and magnitude of the H -statistic may not necessarily identify the degree of market power in a reliable way.⁹⁴

Table A4 displays the results for the Panzar-Rosse H -Statistic with and without control variables. In both cases the estimated H -Statistic, its standard error and its confidence intervals at 95% are very similar. Additionally, Table A4 also shows the p-values for different hypothesis regarding the value of H . The H -Statistic for Mexico takes the value of 0.25. However, we cannot reject that H is zero or negative. Notwithstanding this, we reject that $H = 1$ at the 1% level. In the table we also show the $H - ROA$ market equilibrium test with and without control variables. Since the p-value associated to the hypothesis that $H - ROA = 0$ cannot be rejected, we confirm that the Mexican banking sector shows evidence of market equilibrium. Therefore, we can conclude that the H -Statistic suggest that banks in Mexico behave as if they were best characterized by monopolistic competition.

⁹²We use the following bank-specific characteristics as control variables: average risk weights, ratio of provisions to assets, the ratio of loans to total assets and retail funding to total liabilities.

⁹³We define $H - ROA$ as the H -Statistic estimated using ROA as the dependent variable in eq.(23)

⁹⁴We thank Professor Paolo Coccorese for highlighting the importance of this reference.

Table A5 displays the estimated models for the H -Statistic and $H - ROA$. The estimates are very similar and remain robust to the inclusion of control variables.

A.7 Competition Measures: Boone Indicator

Figure A13 presents the Boone indicator for different sizes of the rolling window. Panel A shows the baseline model where a 1-year rolling window has been used. Panel B and C show the evolution for the Boone with rolling windows of 1.5 years and 2 years. In Panel D we exclude the X_{it} or bank specific control variables from the baseline model. As control variables we used 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.

A.8 Correlation Analysis

The evolution among competition measures varies widely. Table A6 shows the correlation matrix for both TIO and NEIO competition measures. We focus on NEIO measures and discuss a number of findings. Independently of whether we analyze the mean or the median series, both standard and refined Lerner indices have a strong and significant positive correlation with their weighted counterparts. This suggests that the structure of the banking sector when differentiating between D-SIBs and non-D-SIBs is important. Interestingly, the Pearson pairwise correlation coefficient between median (mean) standard Lerner index and its refined counterpart is negative and significant at -0.6 (-0.3). This confirms that there is a weak relationship between the evolution of the competition intensity as measured by the these two Lerner indices. Values reported in the literature by Coccorese (2014, p.80) suggest that there is a weak positive significant correlation of 0.1886. This is possibly due to the presence of returns to scale or bank cost minimization errors. Regarding the Boone indicator, it is uncorrelated with the standard Lerner index⁹⁵ and has a weak positive significant correlation with the refined Lerner index.⁹⁶ Thus, the three analyzed NEIO competition measures suggest different competition intensities, trends and levels.

⁹⁵The insignificant pairwise correlation coefficient between Boone indicator with the standard Lerner mean and median is 0 and 0.1, respectively.

⁹⁶The significant pairwise correlation coefficient between Boone indicator with the refined Lerner index mean and median is 0.2 and 0.3, respectively.

A correlation between any two series should not be seen as static as it changes over time. Moreover, changes in correlation may signal the presence of events that exert a significant impact or they may also identify changes in time series trends. Figure A14 shows how correlations change between the standard and refined Lerner indices over time when using a 36-month rolling window. The range for the overall correlation for the mean (median) is from -0.79 (-0.72) to 0.91 (0.57). Except for the end-of-sample, the pattern is broadly similar. In fact, correlation between the mean of the standard and refined Lerner index is higher than its median counterpart possibly due to the presence of outliers. We focus on the correlation path followed by the median. Surprisingly, correlation between the median standard and refined Lerner indices is negative during 2011 to end-2012; then it turns positive and follows a two humped-process during 2013 to early-2016, and then it turns negative. An event that could possibly explain the shift in correlations is the 2014 financial reform. It could happen that banks anticipated the implementation date. In July 2012, Mexico had presidential elections and candidates already revealed their economic agenda. Notwithstanding this, bank behaviour may differ across bank groups and this may also drive correlations. In general, the correlations between our competition measures indicate that they represent different dimensions of competition. Kick and Prieto (2015) find a similar result for the German banking sector.

Figure A15 and Figure A16 show the 36-month rolling window correlation between YoY change in mean and median between the standard and the refined Lerner index for the banking sector and also for banks grouped by their type, respectively.

A.9 Regression Analysis: Sub-sample Estimation

To assess whether the 2014 financial had any impact on our competition measures, we analyze the evolution of the standard and refined Lerner indices along with the Boone indicator and restrict the sample to three periods: (1) 2008:M01 to 2009:M12, the crisis period which affected the behaviour of at least five Mexican large foreign bank subsidiaries D-SIBs; (2) 2010:M01 to 2013:M12, the post-crisis period; and (3) the financial reform from 2014 onwards. We start by comparing the estimates for the steady state (i.e., full sample) with the estimates in each of the three sub-samples. To ensure consistency in the comparison between time periods (i.e., three sub-samples: crisis, post-crisis and post-reform), we use only banks that existed in the year previous to 2014. In so doing, we decrease any bias introduced by

new bank entries.

Table A7 shows summary statistics for all variables grouped by time period as follows: (i) full sample (i.e. 2008:M1-2019:M3); (ii) Crisis period (i.e. 2008:M1-2019:M12); (iii) Post-crisis period (i.e. 2010:M1-2013:M12); and (iv) Post-financial reform (i.e. 2014:M1-2019:M3). Table A8 presents the multivariate linearly constrained panel regression analysis for the standard Lerner index for the full sample and also for three sub-samples (i.e. the crisis period, the post-crisis period, post-financial reform). In turn, Table A9 shows the multivariate estimations of the fixed effects stochastic frontier model for the refined Lerner index for the full sample and also for the three sub-samples (i.e. the crisis period, the post-crisis period, post-financial reform).

Figure A17 shows the monthly evolution of the median estimate of the unweighted standard Lerner index for the three separate sub-samples overlaid with the 10th, 25th, 75th and 90th percentiles of each period and the median estimate using the entire sample. The median estimate for the crisis period is significantly greater than for the full sample, while the median estimates for the post-crisis and financial reform period are slightly greater. This suggests that price-cost margins were significantly higher during the crisis period. Interestingly, the distribution is significantly wider during the financial reform period.

Figure A18 shows the monthly evolution of the median estimate of the unweighted refined Lerner index for the three separate sub-samples overlaid with the 10th, 25th, 75th and 90th percentiles of each period and the median estimate using the entire sample. The median estimate for the crisis period is initially greater than for the full sample, but then it falls and ends in a lower level. In contrast, the median estimate for the post-crisis period is significantly higher, while the median estimate for the financial reform period is slightly lower. Interestingly, the distribution is significantly wider in the crisis and post-crisis period. These results are opposite to the standard case.

A.10 Regression Analysis: Testing the Exclusion of Investment Banks from Sample

Figures A19 and A20 display the evolution of the unweighted standard and refined Lerner index, respectively excluding certain banking groups.

A.11 Regression Analysis: Stationarity Tests

Table A10 shows the stationarity tests applied to our data for the regression analysis to assess the impact of the 2014 financial reform.

A.12 Linear Regression Analysis Based on the Composite Bank Competition Index

In this paper, we have analyzed the evolution of three NEIO individual aggregate competition measures, namely, the standard and refined Lerner indices, and the Boone indicator. Evidence based on our linear regression framework using the standard Lerner index and the Boone indicator suggests that the financial reform had a statistically significant positive impact on competition. However, evidence based on the refined Lerner index suggests that the financial reform had no impact on competition. These three competition variables have a different information content that is related to the unobservable level of competition in the banking sector. Even-though using individual indicators has its own merit, a partial view arises from analyzing these indicators in isolation. In this regard, a composite indicator synthesises these three competition variables into a single index metric and provides supplementary evidence to assess the overall effect of the financial reform. Composite indicators are used in the economic literature and in policy analysis to monitor the evolution over time and to identify underlying trends. Moreover, use of a composite indicator synthesis complex multi-variate variables into one single metric that is easier to understand (Saisana and Tarantola (2002)).

In this section, we construct a composite competition index using principal components analysis (PCA) to examine competition in the banking sector.⁹⁷ To the best of our knowledge, there is no global multi-country benchmark variable or single-country reference measure of a composite indicator in the banking literature that includes all minimum dimensions of competition using data at the bank or banking sector level. To construct our composite index, we use as input the mean and median values of the annual difference of the standard and refined Lerner indices, and also the annual difference of the Boone indicator. We measure all variables using the annual difference to obtain results that are congruent and consistent with the statistical properties of our regression framework. We use the three NEIO competition mea-

⁹⁷We thank an anonymous referee for highlighting that it is desirable to construct a competition index as a supplement to our analysis, due to the opposite result between the standard and refined Lerner indices.

asures to construct an aggregate composite competition index for the banking sector applying PCA as follows: we choose the first principal component as the competition index for the banking sector. We refrain from including concentration indicators as Claessens and Laeven (2003) shows that the former are a poor proxy of competition variables.

Table A11 shows the weights of the first principal component (eigenvectors) (i.e., our composite index) assigned to each individual competition measure for the mean and median values. The three weights of the first principal component have a positive sign. Interestingly, the size of the refined Lerner index coefficients is markedly different between the mean and median value. We also report in Panel B of Table A11 that the proportion of the total variation explained by the first principal component for the mean (median) value is more (less) than half of the variation in competition. As a reference we also included the proportion of the total variation explained by the second and third principal components. Table A12 provides the summary statistics for both composite competition indices.

Figure A21 shows the evolution of the composite competition index over the sample period from January 2009 to April 2019. A positive sign for the weights of each competition measure suggests that higher values of the composite index are associated with a lower level of competition intensity.

Table A13 and Table A14 display the correlation matrices between the first principal component and the competition variables for the mean and median values, respectively. Interestingly, the correlation among the three input competition variables is low and limited (e.g., with none of the coefficients above 0.4), and this is a pre-requisite to develop a meaningful composite indicator.⁹⁸ All three Pearson pairwise correlation coefficients between the individual competition measures and the composite index are positive. This result suggests that any sign of increasing deterioration in any of the three individual competition indicators is associated with a decrease in competition in the composite index. As expected, the results for the mean and median value differ between the refined Lerner index and the first principal component as the Pearson pairwise correlation is 0.65 for the mean and 0.26 median.

To test whether the financial reform had an impact on our composite competition index, we use this variable as dependent variable and estimate the linear regression model as specified in

⁹⁸Saltelli et al. (2005) argue that highly correlated input variables may lead to a composite indicator characterized by a distortion in its signalling properties due to its design which overemphasises these particular variables.

eq.(17).⁹⁹ Table A15 shows the estimation results. As a reference and to facilitate comparison with previous results, we also report the estimation results available in Table 3 for the three individual competition indicators (i.e., standard and refined Lerner index, and the Boone indicator). The negative and significant coefficient value of the binary indicator variable D_{2t} suggests that the 2014 financial reform decreases the mean (median) value of the annual change of our composite competition index, on average, by 1.66 (1.60) units during our sample period. As in the individual regression analysis available in Section 5.2.7.2, these coefficient estimates are greater to a one standard deviation increase in either the mean (1.26) or median (1.15) values. Hence, we find that the 2014 financial reform has a significant impact on stimulating competition intensity.

It is convenient to take this result with prudence as using composite indicators is not uncontroversial and free from criticism. Zhou et al. (2010) show that aggregation into a single metric may conceal underlying relevant information. Also, the selection of weighting and standardisation of individual indicators is open to user's choice. In fact, the weighting based on principal components analysis may have a number of disadvantages. Depending on the correlation structure, the principal components analysis may assign very low weights to some of the indicators. This is opposed to the initial objective that the composite indicator should capture all dimensions. Also, the design of the PCA weighting can only capture overlapping information between correlated indicators. Thus, weights cannot be estimated when there is only limited correlation. We believe that our application is free from these two flaws related to the weighting of the PCA. Overall, this evidence supports a positive impact of the 2014 financial reform on competition.

A.13 Regression Analysis: Quantile Regression Using Bank-Level Data

Table A16 reports the results from the quantile regression analysis using the bank-level refined Lerner index as dependent variable. Column 2 provides coefficient estimates from traditional linear regression analysis as reference. Overall, except for the specific case of non-DSIBs, results are very similar in comparison with the previous case. For non-DSIBs, we have mixed findings. Results suggest that competition intensity worsened in two out of three quantiles (i.e., p05, p10) that form part of the low market power segment, while com-

⁹⁹Since we use annual difference of the individual competition variables to construct the composite index, we estimate eq.(17) without taking the annual difference in the composite index as this would lead to an over-differentiation of our time series.

petition intensity improved for all banks that form part of the high market power segment. Taken together, due to the fact that the median coefficient estimate has a negative sign and is weakly significant at the 10 percent level, we conclude that this result is not qualitatively distinct from the previous standard Lerner case.

Figure A22 shows the effect of the financial reform per bank type for varying quantiles of the market power measure based on the refined Lerner index. Findings are qualitatively similar to the previous case.

A.14 Markov Switching Models Based on the Composite Bank Competition Index

In this section, we report the estimation results of our simple dynamic Markov switching model. We estimate the model defined in eq.(20) and we use as dependent variable the composite competition indices obtained from PCA. Table A17 shows the estimates for the Markov switching regime change. We find evidence of two persistent and significant regimes for both the mean and median values of the composite competition indicators. Specifically, α_1 and α_2 are the conditional mean of the endogenous variable in state 1 and state 2, respectively. As expected the conditional mean is lower (i.e., high competition intensity) in state 1. Also, the conditional standard deviation in state 1 (i.e., high competition intensity) is higher than in state 2. We also report the value of the transition probability from state 1 to remain in state 1 (i.e., $p_{1,1}$) and the value of the transition probability from state 2 to state 1 (i.e., $p_{2,1}$)¹⁰⁰. Given that $p_{1,1}$ and $p_{2,2}$ are greater than 0.85 for both composite competition indices, we conclude that both competition states are highly persistent. This means that once the process enters any of these two states, it will remain there for a number of periods.

Figure A23 shows the evolution of the composite competition indices as well as each competition measure using the twelve month annual variation (i.e., dark blue solid line). In turn, the red dashed line (plotted in the right hand axis) shows the probability of being in a high competition regime. Also, we include the estimated conditional means of each regime (green dot lines) where the bottom green line denotes the conditional mean in the state of increasing competition. Panel A shows the evolution for the mean value of the composite competition index. We identify four periods of intense competition and these are highlighted in red (i.e.,

¹⁰⁰It is simple to compute the probability of transition from state 2 to state 2 as $p_{2,2} = 1 - p_{2,1}$

the first during 2010, the second during 2011, the third from 2014 to 2016 and the last during 2018 to 2019). Panel B shows results for median value of the composite competition index. Interestingly, we identify two periods of intense competition (i.e., the first during 2014 to 2016 and the second during 2018-2019). Panel C and D (E and F) show the evolution for the annual variation of the mean and median values of the standard (refined) Lerner index, respectively. Panel G shows the evolution of the annual difference in the Boone indicator. The information content available in Panel C to G is taken from Figure 7 to facilitate comparison. All in all, both composite competition indices suggest that there is a period of intense competition starting in 2014. This result provides evidence supporting the view that the 2014 financial reform intensified competition pressures. In addition, the information content of both composite indicators is less noisy compared with the individual competition measures used to construct them.

Table A1: Definition of variables

Variables (<i>symbol</i>) [unit of analysis]	Description	Source (P=Proprietary)
Bank assets (Q_{it}) [MXN in millions]	This variable is used as a measure of bank's scale and total output. For the monthly frequency, it is measured at the individual bank level as the average of the past twelve months of total assets. For the quarterly frequency, it is measured as the end-of-month value reported for each quarter.	CNBV
Bank funding costs ($W_{it}^{(1)}$) [Unit free]	For each bank, the numerator is computed as the sum of the interest expenses during the past twelve months, while the denominator is the average of bank's total asset for the past twelve months. This variable approximates 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) during the past twelve months, while the denominator is the average of bank's total assets during the past twelve months.	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), while the denominator is the average of bank's total assets during the past twelve months.	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 during the past twelve months.	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, during the past twelve months.	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 on this table.	CNBV
Profits to assets ratio (π_{it}) [Unit free]	For each bank, the numerator is computed as the sum of profits during the past twelve months, while the denominator is the banks assets as defined on 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 on 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 on this Table.	Banxico (P) and CNBV

Table A1. (Continued)

Variables (<i>Acronym</i>) (unit of analysis)	Description	Source (P=Proprietary)
Return on assets (ROA_{it}) [Unit free]	For each bank, the numerator is computed profits after tax, while the denominator are the bank's assets as defined on this Table.	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, while the denominator are the bank's assets as defined on this Table.	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, while the denominator is the bank's total asset as defined on this Table.	CNBV
Retail funding to total liabilities ratio. (RF_{it}/TL_{it}) [Unit free]	For each bank, the numerator is the amount of bank's customers total deposits, while the denominator is the bank's total liabilities.	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, while the denominator is the bank's total assets as defined on this Table.	Banxico
Bank-group dummies (BG_i) [Unit free]	This is a set of binary variables that are used to identify banks' business models according to their degree of specialization. Each bank was classified into one of the following four groups: D-SIBs, Investment banks, Mid-Sized banks and Specialized banks. Except for the category of D-SIBs, this not an official classification of Banco de México.	Banxico
Economic activity index (EAI_{it}) [%]	The index of global economic activity (IGAE) is a short-term indicator for GDP. The index is computed as the result of weighted information on production from all the sectors in the economy, and follows the same methodology of the National Accounting System. This series is seasonally adjusted.	INEGI
Unemployment rate (UR_{it}) [%]	This is the unemployment rate of Mexico obtained from the national occupation and employment survey (ENOE, its acronym in Spanish). This series is seasonally adjusted.	INEGI
Inflation rate (IR_{it}) [%]	Computed based on the Consumer Price Index.	INEGI

Source: Banco de México, CNBV and INEGI.

Notes: This table lists the set of dependent variables and covariates, along with their respective definition, that we use to either compute or estimate our competition measures. The last column lists the source of our data where: 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 monthly and quarterly basis. $W_{it}^{(2)}$ is computed based on proprietary information. All other variables are publicly available. For the calculation of $W_{it}^{(1)}$ some authors (see de Ramon and Straughan (2019)) prefer to use total deposits instead of total assets as a variable for the denominator of this ratio. As a robustness check, we have used also used this definition, but our results do not vary.

Table A2: Multivariate linearly constrained panel regression analysis for standard Lerner index

VARIABLES	M1	M2	M3	M4	M5
$\log(Q_{it})$	1.1270*** (0.2077)	0.8411*** (0.1953)	0.9350*** (0.1462)	1.1270*** (0.0320)	1.0625*** (0.1400)
$\log(Q_{it})^2$	-0.0106 (0.0125)	0.0052 (0.0087)	0.0021 (0.0071)	-0.0106*** (0.0018)	-0.0070 (0.0073)
$\log(W_{it}^{(1)})$	0.3076*** (0.0867)	-0.2307 (0.2002)	-0.0880 (0.1445)	0.3076*** (0.0187)	0.3183*** (0.0857)
$\log(W_{it}^{(2)})$	0.2216 (0.1416)	0.4571*** (0.1220)	0.4095*** (0.0992)	0.2216*** (0.0207)	0.2120 (0.1360)
$\log(W_{it}^{(3)})$	0.4707*** (0.1279)	0.7736*** (0.2417)	0.6785*** (0.1602)	0.4707*** (0.0218)	0.4696*** (0.1300)
$\log(Q_{it})\log(W_{it}^{(1)})$	0.0220** (0.0097)	0.0596*** (0.0170)	0.0541*** (0.0132)	0.0220*** (0.0017)	0.0211*** (0.0078)
$\log(Q_{it})\log(W_{it}^{(2)})$	-0.0215 (0.0165)	-0.0443*** (0.0128)	-0.0465*** (0.0122)	-0.0215*** (0.0022)	-0.0207 (0.0161)
$\log(Q_{it})\log(W_{it}^{(3)})$	-0.0005 (0.0135)	-0.0153 (0.0223)	-0.0076 (0.0152)	-0.0005 (0.0022)	-0.0004 (0.0143)
$\log(W_{it}^{(1)})^2$	0.0510*** (0.0144)	0.0016 (0.0216)	0.0241 (0.0166)	0.0510*** (0.0014)	0.0514*** (0.0147)
$\log(W_{it}^{(2)})^2$	-0.0106 (0.0131)	-0.0186 (0.0163)	-0.0247 (0.0187)	-0.0106*** (0.0013)	-0.0111 (0.0144)
$\log(W_{it}^{(3)})^2$	0.0173 (0.0133)	0.0447*** (0.0133)	0.0377*** (0.0123)	0.0173*** (0.0015)	0.0159 (0.0136)
$\log(W_{it}^{(1)})\log(W_{it}^{(2)})$	-0.0116 (0.0101)	0.0309*** (0.0102)	0.0191** (0.0095)	-0.0116*** (0.0012)	-0.0122 (0.0102)
$\log(W_{it}^{(1)})\log(W_{it}^{(3)})$	-0.0394*** (0.0127)	-0.0325* (0.0183)	-0.0432*** (0.0167)	-0.0394*** (0.0013)	-0.0392*** (0.0135)
$\log(W_{it}^{(2)})\log(W_{it}^{(3)})$	0.0222 (0.0162)	-0.0122 (0.0204)	0.0055 (0.0194)	0.0222*** (0.0014)	0.0233 (0.0170)
Bank FE	Yes	No	No	Yes	Yes
Time FE	Yes	No	No	Yes	No
Bank type dummies	No	No	Yes	No	No
<i>Inflation rate_t</i>					0.5785 (0.6640)
<i>Economic growth_t</i>					-0.3683* (0.2235)
<i>Unemployment rate_t</i>					-0.8147 (1.1754)
<i>Constant</i>		2.2822** (0.9943)			

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the multivariate estimates for the standard Lerner index for the five models (i.e. M1 to M5) under analysis. Model M1, M2, M3 and M5 were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. All estimations were done in Stata using the command 'cnreg' which is used for constrained linear panel regressions along with different options available in the software as discussed in section 4.2. All estimations are based on eq.(2). We have an unbalanced panel of 4,507 bank-month observations that cover the period from January 2008 to March 2019. Time fixed effects were introduced to control for heterogeneity for each month. Bank type fixed effects were introduced to take into account heterogeneity across four different bank business models.

Table A3: Multivariate estimation of the fixed effects stochastic frontier model for the Refined Lerner index

VARIABLES	M1	M2	M3	M4	M5
$\log(Q_{it})$	0.0811 (0.0592)	0.0345*** (0.0015)	0.0823 (0.0631)	0.0789 (0.0587)	0.0811*** (0.0084)
$\log(W_{it}^{(1)}/W_{it}^{(3)})$	-0.0619 (0.0450)	0.0027 (0.0023)	-0.0605 (0.0485)	-0.0631 (0.0454)	-0.0619*** (0.0045)
$\log(W_{it}^{(2)}/W_{it}^{(3)})$	0.0278 (0.0239)	-0.0194*** (0.0018)	0.0284 (0.0236)	0.0314 (0.0214)	0.0278*** (0.0034)
T	-0.0000 (0.0006)	0.0002*** (0.0001)	0.0003 (0.0007)	0.0002 (0.0007)	-0.0000 (0.0001)
Provisions to assets _{it}				-0.2633 (1.1084)	
Loans to assets _{it}				0.0761 (0.1465)	
Retail funding to total liabilities _{it}				-0.1092 (0.0885)	
Average risk weights _{it}				-0.0669 (0.0940)	
Inflation rate _t			0.2584 (0.5918)	0.4737 (0.5614)	
Econ. growth _t			-0.0677 (0.3235)	-0.0425 (0.3153)	
Unemployment rate _t			1.9001 (1.6991)	1.0484 (1.3168)	
Constant		0.5413*** (0.0172)			
σ^2	0.0465*** (0.0147)	0.0981*** (0.0026)	0.0466*** (0.0148)	0.0479*** (0.0159)	0.0465*** (0.0015)
λ	1.8145*** (0.5276)	3.1837*** (0.0060)	1.8325*** (0.5274)	2.5049*** (0.7462)	1.8145*** (0.0741)
Bank FE	Yes	No	Yes	Yes	Yes
Observations	4,503	4,503	4,503	4,503	4,503

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table shows the multivariate estimates for the estimation of the fixed effects stochastic frontier model for the refined Lerner index for the period January 2008 to March 2019. All estimations were done in Stata using the commands 'sftfe' (see Chen et al. (2014) and Belotti and Ilardi (2018)) and 'frontier' which are used for stochastic frontier analysis. All estimations are based on eq.(11). Parameter λ is the share of technical inefficiency in the total error variance, while σ^2 is the total error variance. Model M1 is our baseline where fixed effects by individual bank to account for heterogeneity have been included. Model M2 is estimated with a pooled approach (i.e. excluding bank fixed effects). Model M3 is M1 with macroeconomic controls. Model M4 is M3 with bank-level control variables. Model M5 is the same as our baseline (i.e. M1) excluding clustered standard errors grouped by bank. Except for model M5, all remaining models were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks.

Table A4: Panzar-Rosse H -Statistic results

Model	Statistic	Coeff.	S.E.	Confidence intervals 95%	p-values			
					$H_0: H = 0$	$H_0: H > 0$	$H_0: H < 0$	$H_0: H = 1$
Without control variables	H -statistic	0.3005	0.2498	(-0.2036,0.8048)	0.2356	0.8821	0.1178	0.0077
	H -ROA	-0.0043	0.0048	(-0.0140,0.0053)	0.3725	0.1862	0.8137	0
With control variables	H -statistic	0.2559	0.2262	(-0.2007,0.7126)	0.2644	0.8677	0.1322	0.0020
	H -ROA	-0.0046	0.0058	(-0.0164,0.0070)	0.4260	0.2133	0.7866	0

Source: Banco de México, authors' calculations.

Notes: This table displays the estimates for the Panzar-Rosse H Statistic and for the $H - ROA$ long run equilibrium test for the models with and without control variables. Moreover, the table also shows the p-values associated to different one-side and two-side alternatives for the H -Statistic. The H -Statistic and the $H - ROA$ were estimated and calculated following eq.(23) and eq.(24). The models were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. We have an unbalanced panel of 4,424 bank-month observations that cover the period from January 2008 to March 2019. Time fixed effects were introduced to control for heterogeneity for each month. Bank type fixed effects were introduced to take into account heterogeneity across four different bank business models.

Table A5: Panzar-Rosse H -statistic estimations

VARIABLES	H	$H - ROA$	H	$H - ROA$
$\log(W_{it}^{(1)})$	0.253** (0.108)	-0.00113 (0.00267)	0.211 (0.126)	-0.00121 (0.00260)
$\log(W_{it}^{(2)})$	-0.00399 (0.0622)	0.00358 (0.00324)	0.00245 (0.0560)	0.00337 (0.00299)
$\log(W_{it}^{(3)})$	0.0514 (0.163)	-0.00680 (0.00571)	0.0428 (0.136)	-0.00684 (0.00621)
Provisions to assets $_{it}$			6.173** (2.431)	0.0462 (0.213)
Loans to assets $_{it}$			-0.220 (0.402)	0.0192 (0.0211)
Retail funding to total liabilities $_{it}$			0.777** (0.309)	-0.0119 (0.0109)
Average risk weight $_{it}$			-0.386 (0.279)	-0.00210 (0.0109)
R-squared	0.664	0.085	0.706	0.097

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table shows the estimates for the Panzar-Rosse model for the period January 2008 to March 2019. We use two definitions for the dependent variable. The traditional H -statistic use the bank's total revenues as dependent variable and this is an unscaled measure. In contrast, $H - ROA$ -statistic use the bank's return on total assets as dependent variable, which is a scaled measure. All models were estimated using bank and time fixed effects with clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. All estimations were done in Stata using the command 'xtreg' which is used for fixed effects linear panel regressions. All estimations are based on eq.(23). Time fixed effects were introduced to control for heterogeneity for each month. Bank fixed effects were introduced to take into account heterogeneity across banks. We have an unbalanced panel of 4,424 bank-month observations. Models in column 4 and 5 include bank-level control variables.

Table A6: Correlation matrix between competition measures

#	Variable	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
1	Number of banks	-0.6 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	0.6 ^a	0.4 ^a	0.9 ^a	0.8 ^a	0.8 ^a	0.8 ^a	0.9 ^a	0.8 ^a	-0.5 ^a	-0.7 ^a	-0.1	-0.3 ^a	0	0	-0.1	-0.1	-0.1		
2	CR ₇ by assets		0.8 ^a	0.8 ^a	0.8 ^a	0.7 ^a	0.7 ^a	-0.9 ^a	-0.8 ^a	-0.5 ^a	-0.7 ^a	-0.7 ^a	-0.8 ^a	-0.5 ^a	-0.7 ^a	0.5 ^a	0.4 ^a	0.4 ^a	0.3 ^a	0.1	0.1	0.3 ^a	0.3 ^a	0.1		
3	CR ₇ by loans			1 ^a	1 ^a	1 ^a	1 ^a	-0.7 ^a	-0.6 ^a	-0.7 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.7 ^a	-0.9 ^a	0.5 ^a	0.5 ^a	0.2 ^b	0.2 ^c	0	-0.1	0.2 ^c	0.1	0.1		
4	CR ₇ by deposits				1 ^a	1 ^a	1 ^a	-0.8 ^a	-0.6 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.9 ^a	-0.8 ^a	-0.9 ^a	0.5 ^a	0.6 ^a	0.3 ^a	0.3 ^a	0.1	0.1	0.2 ^a	0.2 ^b	0.1		
5	HHI assets					0.9 ^a	1 ^a	-0.8 ^a	-0.7 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.9 ^a	-0.8 ^a	-0.9 ^a	0.5 ^a	0.6 ^a	0.3 ^a	0.3 ^a	0.1	0.1	0.2 ^a	0.3 ^a	0.1		
6	HHI deposits						1 ^a	-0.7 ^a	-0.6 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	0.5 ^a	0.6 ^a	0.2 ^b	0.3 ^a	0	0	0.2 ^c	0.1	0.1		
7	HHI loans							-0.7 ^a	-0.6 ^a	-0.8 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	-0.8 ^a	-0.9 ^a	0.5 ^a	0.6 ^a	0.2 ^b	0.2 ^b	0	0	0.2 ^c	0.1	0.1		
8	Median Lerner standard (MLS)								0.9 ^a	0.6 ^a	0.7 ^a	0.7 ^a	0.7 ^a	0.5 ^a	0.7 ^a	-0.6 ^a	-0.4 ^a	-0.5 ^a	-0.4 ^a	-0.3 ^a	-0.2 ^a	-0.5 ^a	-0.4 ^a	0		
9	Mean Lerner standard (mls)									0.5 ^a	0.6 ^a	0.6 ^a	0.6 ^a	0.5 ^a	0.6 ^a	-0.5 ^a	-0.3 ^a	-0.5 ^a	-0.4 ^a	-0.3 ^a	-0.3 ^a	-0.5 ^a	-0.4 ^a	0.1		
10	Weighted MLS by assets										0.7 ^a	0.9 ^a	0.7 ^a	1 ^a	0.7 ^a	-0.5 ^a	-0.7 ^a	-0.2 ^b	-0.4 ^a	0	-0.1	-0.1 ^c	-0.2 ^a	-0.2 ^c		
11	Weighted mls by assets											0.8 ^a	1 ^a	0.7 ^a	1 ^a	-0.7 ^a	-0.5 ^a	-0.3 ^a	0	-0.2 ^b	0.1	-0.3 ^a	0	0		
12	Weighted MLS by loans												0.8 ^a	0.9 ^a	0.8 ^a	-0.5 ^a	-0.7 ^a	-0.2 ^a	-0.4 ^a	0	-0.1	-0.2 ^b	-0.3 ^a	-0.2 ^c		
13	Weighted mls by loans													0.7 ^a	1 ^a	-0.7 ^a	-0.6 ^a	-0.3 ^a	-0.1	-0.1	0.1	-0.3 ^a	-0.1	0		
14	Weighted MLS by deposits														0.8 ^a	-0.4 ^a	-0.6 ^a	-0.2 ^c	-0.4 ^a	0	-0.1	-0.1	-0.2 ^b	-0.2 ^b		
15	Weighted mls by deposits															-0.7 ^a	-0.6 ^a	-0.3 ^a	-0.1	-0.1	0.1	-0.3 ^a	0	0		
16	Median Lerner refined (MLR)																0.8 ^a	0.6 ^a	0.4 ^a	0.4 ^a	0.4 ^a	0.6 ^a	0.5 ^a	0.2 ^c		
17	Mean Lerner refined (mlr)																		0.4 ^a	0.7 ^a	0.2 ^b	0.5 ^a	0.4 ^a	0.6 ^a	0.3 ^a	
18	Weighted MLR by assets																			0.6 ^a	0.9 ^a	0.8 ^a	1 ^a	0.7 ^a	0.1	
19	Weighted mlr by assets																					0.4 ^a	0.9 ^a	0.5 ^a	0.9 ^a	0.3 ^a
20	Weighted MLR by loans																						0.7 ^a	0.9 ^a	0.6 ^a	0.1
21	Weighted mlr by loans																							0.7 ^a	1 ^a	0.2 ^b
22	Weighted MLR by deposits																								0.7 ^a	0.1 ^c
23	Weighted mlr by deposits																									0.3 ^a
24	Boone indicator																									

Source: Banco de México, authors' calculations.

Notes: a (b) [c] significant at 1% (5%) [10%] level. This table displays the pairwise Pearson correlation matrix between both TIO and NEIO competition measures and its statistical significance as well as the hypothesis test that Pearson correlation coefficient it is zero.

Table A7: Descriptive statistics of micro and macro variables for different periods

Variable	Full sample 2008:M1-2019:M3			Crisis 2008:M1-2009:M12			Post-crisis 2010:M1-2013:M12			Post financial reform 2014:M1-2019:M3		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Dependent variables												
Total costs (C_{it})	16.07	3.85	29.02	14.75	3.31	26.34	14.02	3.27	25.32	19.62	5.66	33.39
Revenues to costs ratio (RC_{it})	1.16	1.12	0.23	1.12	1.09	0.20	1.17	1.13	0.24	1.19	1.15	0.23
Total revenues (TR_{it})	19.17	4.50	35.47	17.50	3.94	31.69	16.45	3.79	29.87	23.52	6.37	41.47
Return on assets ^c (ROA_{it})	0.01	0.01	0.03	0.01	0.01	0.05	0.02	0.01	0.03	0.01	0.01	0.02
Profits to assets ratio (π_{it})	0.02	0.01	0.04	0.02	0.01	0.06	0.02	0.01	0.04	0.02	0.01	0.03
Independent variables												
<i>Input prices</i>												
Bank funding costs ($W_{it}^{(1)}$)	0.04	0.03	0.03	0.06	0.05	0.04	0.03	0.03	0.01	0.04	0.03	0.03
Bank labor expenses ($W_{it}^{(2)}$)	0.03	0.01	0.05	0.03	0.02	0.05	0.02	0.01	0.03	0.03	0.01	0.06
Operational costs ($W_{it}^{(3)}$)	0.04	0.02	0.07	0.04	0.02	0.05	0.04	0.02	0.07	0.05	0.02	0.07
<i>Other bank-level variables</i>												
Total assets (Q_{it})	177.91	34.88	345.08	139.62	28.50	265.44	157.55	30.50	299.73	223.44	52.98	409.17
Revenues to assets ratio (P_{it})	0.15	0.10	0.14	0.17	0.11	0.13	0.14	0.10	0.13	0.16	0.10	0.15
Costs to revenues ratio (\hat{C}_{it})	0.89	0.89	0.17	0.92	0.92	0.17	0.88	0.89	0.16	0.86	0.87	0.13
Provisions to assets ratio (PR_{it}/Q_{it})	0.02	0.02	0.03	0.02	0.01	0.02	0.03	0.02	0.03	0.02	0.01	0.03
Loans to assets ratio (L_{it}/Q_{it})	0.39	0.37	0.25	0.36	0.33	0.25	0.35	0.34	0.26	0.39	0.40	0.24
Retail funding to liabilities ratio (RF_{it}/LR_{it})	0.50	0.53	0.27	0.46	0.45	0.27	0.48	0.50	0.28	0.54	0.57	0.26
Average risk weight (ARW_{it})	0.67	0.63	0.31	0.63	0.59	0.33	0.66	0.62	0.31	0.66	0.62	0.28
<i>Macroeconomic variables</i>												
Economic growth (EG_t)	0.02	0.02	0.03	-0.01	0.01	0.04	0.03	0.04	0.02	0.02	0.02	0.01
Unemployment rate (UR_t)	0.04	0.04	0.01	0.04	0.04	0.01	0.05	0.05	0.00	0.04	0.04	0.01
Inflation rate (IR_t)	0.04	0.04	0.01	0.05	0.05	0.01	0.04	0.04	0.01	0.04	0.04	0.01

Source: Banco de México, authors' calculations.

Notes: This table reports monthly descriptive statistics (i.e. mean, median, standard deviation (S.D.)) of all micro and macro variables for the full sample (i.e. 2008:M1-2019:M3), the crisis period (i.e. 2008:M1-2009:M12), the post-crisis period (i.e. 2010:M1-2013:M12) and the post financial reform period (i.e. 2014:M1-2019:M3). All variables are unit free except for total costs, total revenue and total assets which are reported in thousands of millions (i.e. in B or 10^9 or 'one thousand million' in North America) in Mexican pesos (i.e. MXN). For the full sample statistics we used all the banks available in our sample. To ensure consistency in the comparison between different time periods (i.e. three sub-samples: crisis, post-crisis and post-reform), we used only banks that existed in the year previous to 2014. In so doing, we decrease any bias introduced by new bank entries.

Table A8: Multivariate linearly constrained panel regression analysis for standard Lerner index for different time periods

VARIABLES	Full sample 2008:M1-2019:M3	Crisis 2008:M1-2009:M12	Post-crisis 2010:M1-2013:M12	Post financial reform 2014:M1-2019:M3
$\log(Q_{it})$	1.1077*** (0.2191)	0.6180* (0.3258)	0.8524*** (0.3106)	1.8623*** (0.5609)
$\log(Q_{it})^2$	-0.0093 (0.0136)	0.0018 (0.0165)	-0.0006 (0.0198)	-0.0458* (0.0267)
$\log(W_{it}^{(1)})$	0.3501*** (0.1001)	0.5256*** (0.1949)	0.2524 (0.1939)	0.1244 (0.3117)
$\log(W_{it}^{(2)})$	0.2113 (0.1387)	0.4938 (0.3221)	0.2532* (0.1303)	0.0175 (0.3304)
$\log(W_{it}^{(3)})$	0.4385*** (0.1493)	-0.0195 (0.3003)	0.4945** (0.1989)	0.8581*** (0.3123)
$\log(Q_{it})\log(W_{it}^{(1)})$	0.0170 (0.0166)	0.0176 (0.0205)	0.0235 (0.0252)	0.0440 (0.0284)
$\log(Q_{it})\log(W_{it}^{(2)})$	-0.0200 (0.0168)	-0.0341 (0.0373)	-0.0189 (0.0169)	0.0180 (0.0345)
$\log(Q_{it})\log(W_{it}^{(3)})$	0.0030 (0.0163)	0.0165 (0.0344)	-0.0046 (0.0233)	-0.0619* (0.0365)
$\log(W_{it}^{(1)})^2$	0.0458* (0.0250)	0.0895*** (0.0181)	0.0245 (0.0307)	0.0754*** (0.0315)
$\log(W_{it}^{(2)})^2$	-0.0101 (0.0145)	0.0185** (0.0083)	0.0003 (0.0111)	0.0158 (0.0124)
$\log(W_{it}^{(3)})^2$	0.0184 (0.0140)	0.0040 (0.0143)	0.0356** (0.0146)	-0.0226 (0.0288)
$\log(W_{it}^{(1)})\log(W_{it}^{(2)})$	-0.0087 (0.0137)	-0.0520*** (0.0147)	0.0054 (0.0163)	-0.0569** (0.0267)
$\log(W_{it}^{(1)})\log(W_{it}^{(3)})$	-0.0372** (0.0166)	-0.0375*** (0.0123)	-0.0299 (0.0212)	-0.0185 (0.0194)
$\log(W_{it}^{(2)})\log(W_{it}^{(3)})$	0.0188 (0.0230)	0.0335*** (0.0100)	-0.0057 (0.0203)	0.0411 (0.0274)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	4,245	626	1,590	2,029
p-value F statistic	0	0	0	0
RMSE	0.110	0.0460	0.0857	0.0803

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the multivariate estimates for the standard Lerner index for the full sample and also for three sub-samples. All estimations were done in Stata using the command 'cnreg' which is used for constrained linear panel regressions. All estimations are based on eq.(2). Time fixed effects were introduced to control for heterogeneity for each month. All the specifications were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. In a nutshell, the four estimated models correspond to M1 as described in Appendix A, Table A2. To estimate the cost parameters of all four models (i.e. for the full sample, crisis, post-crisis and post financial reform), we used only the banks that existed in the year previous to 2014. This was done to mitigate any influence from new bank entries.

Table A9: Multivariate estimation of the fixed effects stochastic frontier model for the refined Lerner index for different time periods

VARIABLES	Full sample 2008:M1-2019:M3	Crisis 2008:M1-2009:M12	Post-crisis 2010:M1-2013:M12	Post financial reform 2014:M1-2019:M3
$\log(Q_{it})$	0.0760 (0.0603)	-0.0980 (0.0949)	0.1518 (0.1479)	0.0213 (0.0729)
$\log(W_{it}^{(1)}/W_{it}^{(3)})$	-0.0688 (0.0473)	-0.0256 (0.0518)	-0.1080 (0.1330)	-0.0109 (0.0206)
$\log(W_{it}^{(2)}/W_{it}^{(3)})$	0.0299 (0.0245)	0.0576 (0.0809)	0.0057 (0.0343)	0.0473 (0.0292)
T	0.0000 (0.0007)	0.0022 (0.0024)	-0.0003 (0.0020)	-0.0001 (0.0010)
σ^2	0.0483*** (0.0154)	0.0263*** (0.0076)	0.0649** (0.0264)	0.0128*** (0.0041)
λ	1.8169*** (0.5307)	8.7636** (4.1304)	3.5535*** (1.3142)	1.3150*** (0.3602)
Bank FE	Yes	Yes	Yes	Yes
Observations	4,241	626	1,589	2,026

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the multivariate estimates for the refined Lerner index for the full sample and for three sub-samples (i.e. crisis, post-crisis, post-financial reform). All estimations were done in Stata using the command 'sftfe' (see Chen et al. (2014) and Belotti and Ilardi (2018)) which is used for stochastic frontier analysis. All estimations are based on eq.(11). All the specifications were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. Parameter λ is the share of technical inefficiency in the total error variance, while parameter σ^2 is the total error variance. In a nutshell, the four estimated models correspond to M1 as described in Appendix A, Table A3. To estimate the parameters of all models (i.e. for the full sample, crisis, post-crisis and post financial reform), we used only the banks that existed in the year previous to 2014. This was done to mitigate any influence from new bank entries.

Table A10: Dickey-Fuller unit root tests

	DFA statistic	MacKinnon p-value	1% Crit. Val.	5% Crit. Val.	10% Crit. Val.
Panel A: dependent variables measured in levels (y_t)					
Mean standard Lerner	-1.62	0.47	-3.5	-2.89	-2.58
Median standard Lerner	-1.77	0.39	-3.5	-2.89	-2.58
Mean refined Lerner	-1.81	0.38	-3.5	-2.89	-2.58
Median refined Lerner	-2.21	0.2	-3.5	-2.89	-2.58
Boone indicator	-3.31	0.01	-3.5	-2.89	-2.58
Panel B: dependent variables measured in annual difference ($\nabla_{12}y_t$)					
Mean standard Lerner	-2.99	0.04	-3.5	-2.89	-2.58
Median standard Lerner	-3.88	0	-3.5	-2.89	-2.58
Mean refined Lerner	-3.12	0.03	-3.5	-2.89	-2.58
Median refined Lerner	-3.22	0.02	-3.5	-2.89	-2.58
Boone indicator	-2.89	0.04	-3.5	-2.89	-2.58
Panel C: Macroeconomic variables					
Economic growth	-3.25	0.02	-3.5	-2.89	-2.58
Inflation rate	-2.98	0.04	-3.5	-2.89	-2.58
Unemployment	-0.93	0.78	-3.5	-2.89	-2.58
Annual change in unemployment	-3.81	0	-3.5	-2.89	-2.58
Panel D: Residual (From regression eq.(17))					
Mean standard Lerner	-3.9	0	-3.5	-2.89	-2.58
Median standard Lerner	-4.32	0	-3.5	-2.89	-2.58
Mean refined Lerner	-3.64	0	-3.5	-2.89	-2.58
Median refined Lerner	-4.68	0	-3.5	-2.89	-2.58
Boone indicator	-3.33	0.01	-3.5	-2.89	-2.58

Source: Banco de México, authors' calculations.

Notes: We use the command "dfuller" in STATA to perform the augmented Dickey-Fuller unit-root test. The null hypothesis is that the variable has a unit root that is driven by a random walk without drift. We include a constant term, but we do not include a deterministic time trend as there is no reason to support its inclusion. This is because we don't have evidence of an upward trend. We used Akaike Information Criterion (AIC) as a guide to determine the number of lags to be included in ADF regression. STATA reports for ADF test, MacKinnon's approximate p-value for the test statistic Z(0). The annual difference operator refers to the value of the variable at time "t" minus the value at time "t-12". Economic growth rate and inflation rate were calculated as annual difference in percent, this is the value at time "t" divided by the value at time "t-12" minus one or $\nabla_{12}X_t/X_{t-12} = (1-L^{12})X_t/X_{t-12} = (X_t - X_{t-12})/X_{t-12} = X_t/X_{t-12} - 1$ where L is the lag operator. The unemployment rate is the annual difference between the unemployment rate at time "t" minus its value at time "t-12".

Table A11: Principal components eigenvectors and proportion of total variation explained

Principal components (eigenvectors)	Mean	Median
<i>Panel A: Eigenvectors</i>		
Standard Lerner	0.64	0.66
Refined Lerner	0.51	0.22
Boone indicator	0.58	0.71
<i>Panel B: proportion of total variation explained</i>		
First Component	0.53	0.44
Second Component	0.27	0.34
Third Component	0.20	0.22

Source: Banco de México, authors' calculations.

Notes: This table reports in Panel A the eigenvectors associated to the first principal component of the standard and refined Lerner indices and the Boone indicator. We measure our competition variables using the annual difference. Panel B reports the total variation explained per component.

Table A12: Descriptive statistics of the composite competition index

Variable	Mean	Std Dev	Min.	Q. 25	Median	Q. 75	Max
Mean PCA	0.00	1.26	-2.80	-0.80	-0.12	0.74	3.00
Median PCA	0.00	1.15	-2.42	-0.82	-0.03	0.75	2.89

Source: Banco de México, authors' calculations.

Notes: This table reports the summary statistics for the mean and median values of the composite competition index.

Table A13: Correlation matrix between competition measures based on their mean value

	1	2	3	4
1 Standard Lerner	1			
2 Refined Lerner	0.31 ^a	1		
3 Boone indicator	0.38 ^a	0.19 ^b	1	
4 Composite index	0.8 ^a	0.65 ^a	0.72 ^a	1

Source: Banco de México, authors' calculations.

Notes: a) b) c) significant at 1% (5%) [10%] level. This table displays the pairwise Pearson correlation matrix between the mean values of our competition indicators (measured in annual difference) and the composite index. We include the statistical significance of the hypothesis test that the Pearson correlation coefficient is zero.

Table A14: Correlation matrix between competition measures based on their median value

	1	2	3	4
1 Standard Lerner	1			
2 Refined Lerner	-0.02	1		
3 Boone indicator	0.30 ^a	0.12	1	
4 Composite index	0.76 ^a	0.26 ^a	0.82 ^a	1

Source: Banco de México, authors' calculations.

Notes: a) b) c) significant at 1% (5%) [10%] level. This table displays the pairwise Pearson correlation matrix between the median values of our competition indicators (measured in annual difference) and the composite index. We include the statistical significance of the hypothesis test that the Pearson correlation coefficient is zero.

Table A15: Impact of the financial reform on the composite bank competition index at aggregate level

Variables	PCA		Standard Lerner		Refined Lerner		Boone
	Mean	Median	Mean	Median	Mean	Median	
Economic growth _t	-0.3472*** (0.1298)	-0.2690*** (0.0947)	-0.0006 (0.0019)	0.0004 (0.0015)	-0.0007 (0.0011)	-0.0005 (0.0008)	-0.0083*** (0.0023)
Inflation rate _t	0.1286 (0.1426)	0.1298 (0.1547)	-0.0059*** (0.0018)	-0.0014 (0.0024)	0.0041*** (0.0008)	0.0038*** (0.0009)	0.0022 (0.0041)
∇_{12} Unemployment rate _t	-0.8626** (0.3948)	-1.0346*** (0.3320)	-0.0004 (0.0056)	0.0045 (0.0053)	-0.0019 (0.0029)	-0.0069** (0.0033)	-0.0511*** (0.0086)
D_{1t}			-0.0147 (0.0284)	-0.0144 (0.0225)	-0.0019 (0.0117)	-0.0088 (0.0085)	
D_{2t}	-1.6648*** (0.3992)	-1.6032*** (0.3297)	-0.0260*** (0.0056)	-0.0221*** (0.0046)	-0.0023 (0.0033)	-0.0013 (0.0032)	-0.0306*** (0.0085)
α	1.2482 (0.8469)	0.9500 (0.7460)	0.0440*** (0.0104)	0.0239** (0.0111)	-0.0145** (0.0064)	-0.0151*** (0.0055)	0.0185 (0.0200)
Observations	111	111	121	121	121	121	111
R-squared	0.33	0.37	0.47	0.38	0.26	0.3	0.32
Wald-statistic	5.29***	7.11***	14.53***	8.24***	7.26***	8.11***	12.89***

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table shows the linear regression estimates to assess the impact of the 2014 financial reform on our composite banking sector index. As a reference, to assist the reader, we also include in Column 3 to 7 the regression results for the NEIO competition measures measured in annual difference at the individual level. The composite banking sector index is obtained from three competition variables measured in annual difference. Since the index has values characterized by annual changes, it is not necessary or convenient to take the annual difference of this variable to estimate the linear regression model. We include the R-squared statistic to assess the goodness of fit and the Chi² statistic to test the null hypothesis that all coefficients are equal to zero. The coefficients D_{1t} for the global financial crisis is not available for the Principal Components (PCA) indicator and for the Boone indicator due to sample restrictions. In fact, we only have a few observations available of the first principal component and the Boone indicator from mid-2009 onwards. HAC standard error are in parenthesis.

Table A16: Quantile regression: using bank-level refined Lerner as dependent variable

Variables	OLS	Low market power segment (High competition)			High market power segment (Low competition)			
	(2)	p05 (3)	p10 (4)	p25 (5)	p50 (6)	p75 (7)	p90 (8)	p95 (9)
<i>Interaction terms</i>								
$D_{2t} \times D-SIBs_i$	0.0061 (0.0054)	0.0472*** (0.0140)	0.0130** (0.0056)	0.0078** (0.0032)	0.0046** (0.0021)	0.0024 (0.0019)	-0.0090 (0.0070)	-0.0187 (0.0169)
$D_{2t} \times \text{Non D-SIBs}_i$	-0.0014 (0.0036)	0.0361*** (0.0119)	0.0144** (0.0071)	-0.0016 (0.0024)	-0.0026* (0.0015)	-0.0102*** (0.0024)	-0.0246*** (0.0054)	-0.0318*** (0.0047)
$D_{2t} \times \text{Investment banks}_i$	-0.0090 (0.0181)	0.1400*** (0.0334)	0.0947** (0.0379)	0.0069 (0.0087)	-0.0056 (0.0079)	-0.0407*** (0.0086)	-0.0972*** (0.0143)	-0.1080*** (0.0279)
<i>Bank group binary indicators</i>								
D-SIBs _i	-0.0069 (0.0194)	0.1377*** (0.0335)	0.1236*** (0.0371)	0.0213** (0.0084)	-0.0105 (0.0076)	-0.0563*** (0.0086)	-0.1220*** (0.0175)	-0.1339*** (0.0234)
Non D-SIBs _i	-0.0047 (0.0187)	0.1276*** (0.0312)	0.1115*** (0.0378)	0.0232*** (0.0078)	-0.0057 (0.0074)	-0.0457*** (0.0092)	-0.1027*** (0.0161)	-0.1206*** (0.0229)
<i>Macroeconomic and global crisis controls</i>								
Economic growth _t	-0.0659 (0.1099)	0.1439 (0.1557)	0.1674 (0.1429)	-0.1118 (0.0705)	-0.0071 (0.0555)	0.0604 (0.0709)	-0.0099 (0.1945)	-0.4286 (0.3630)
Inflation rate _t	0.3073*** (0.0862)	0.2168 (0.2735)	0.3637*** (0.1154)	0.3388*** (0.0903)	0.2418*** (0.0448)	0.2764*** (0.0596)	0.3522** (0.1464)	0.3278 (0.2297)
$\nabla_{12} \text{Unemployment}_t$	-0.0511 (0.3212)	0.0092 (0.4852)	0.0443 (0.3440)	-0.3779 (0.2537)	-0.3285** (0.1608)	-0.2291 (0.2398)	0.4353 (0.5466)	0.0815 (0.8587)
D_{1t}	-0.0094 (0.0125)	0.0443*** (0.0156)	0.0050 (0.0123)	-0.0240*** (0.0064)	-0.0189*** (0.0061)	-0.0139** (0.0065)	-0.0232 (0.0144)	-0.0574** (0.0275)
<i>Bank-level controls</i>								
$\nabla_{12} \text{Average risk weight}_{i,t}$	-0.0405** (0.0189)	-0.1053*** (0.0220)	-0.0723*** (0.0254)	-0.0200 (0.0130)	-0.0254*** (0.0073)	-0.0317*** (0.0078)	-0.0489*** (0.0105)	-0.0629*** (0.0103)
$\nabla_{12} \text{Loan to assets ratio}_{i,t}$	0.0611** (0.0250)	0.1044 (0.0670)	0.1186*** (0.0410)	0.0378* (0.0224)	0.0374*** (0.0107)	0.0752*** (0.0168)	0.0877*** (0.0137)	0.0928*** (0.0233)
$\nabla_{12} \text{Retail funding to liabilities ratio}_{i,t}$	0.0175 (0.0159)	0.0333 (0.0207)	0.0115 (0.0134)	0.0059 (0.0182)	0.0147 (0.0098)	0.0040 (0.0110)	0.0144 (0.0140)	0.0615*** (0.0139)
$\nabla_{12} \text{Provision ratio}_{i,t}$	-0.3831* (0.2290)	0.3600 (0.4260)	-0.5011 (0.4058)	-0.4628** (0.1908)	-0.3843*** (0.0770)	-0.3846*** (0.1185)	-0.5170** (0.2449)	-0.5050*** (0.1619)
α	-0.0078 (0.0191)	-0.2443*** (0.0387)	-0.1888*** (0.0383)	-0.0532*** (0.0072)	-0.0029 (0.0073)	0.0571*** (0.0078)	0.1468*** (0.0147)	0.2009*** (0.0273)
$R^2/\text{Pseudo } R^2$	0.017	0.11	0.06	0.03	0.02	0.04	0.09	0.12
F-test of equality of all coefficients								
F-test $D_{2t} \times D-SIBs$		4.59***						
F-test $D_{2t} \times \text{Non D-SIBs}$		10.75***						
F-test $D_{2t} \times \text{Investment banks}$		9.31***						

Table A16 (Continued)

Variables	OLS	Low market power segment (High competition)				High market power segment (Low competition)		
	(2)	p05 (3)	p10 (4)	p25 (5)	p50 (6)	p75 (7)	p90 (8)	p95 (9)
F-test of pairwise equality of coefficients estimates on $D_{2t} \times$ D-SIBs between quantiles								
p05			4.17**	5.47**	6.47**	6.08**	9.68***	8.26***
p10				1.24	3.45*	4.55**	9.97***	3.11*
p25					1.46	2.68	5.48**	2.32
p50						0.78	4.36**	1.89
p75							3.01*	1.63
p90								0.5
F-test of pairwise equality of coefficients estimates on $D_{2t} \times$ Non D-SIBs between quantiles								
p05			5.07**	9.99***	10.41***	15.79***	28.86***	39.02***
p10				12.42***	10.98***	23.83***	50.59***	42.32***
p25					0.14	8.15***	22.68***	23.50***
p50						16.94***	23.81***	35.76***
p75							13.21***	22.76***
p90								3.17*
F-test of pairwise equality of coefficients estimates on $D_{2t} \times$ Investment banks between quantiles								
p05			1.44	25.03***	30.89***	43.76***	88.60***	34.45***
p10				6.24**	7.14***	14.03***	26.46***	25.46***
p25					3.27*	20.45***	41.64***	17.58***
p50						13.23***	33.98***	12.17***
p75							16.34***	6.32**
p90								0.2

Source: Banco de México, authors' calculations.

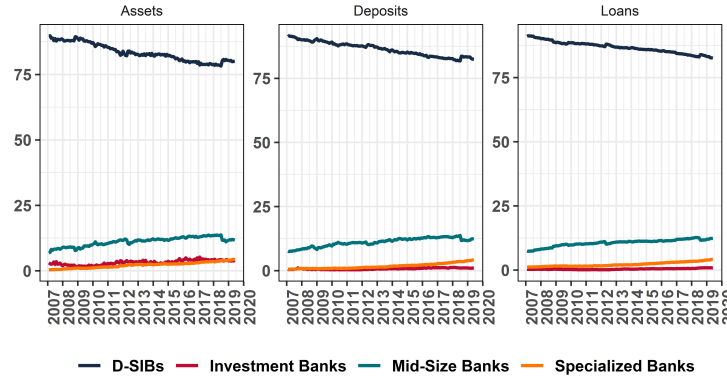
Notes: *** (**) [*] significant at 1% (5%) [10%] level. This table displays linear and quantile regression results. The dependent variable in all specifications is the refined Lerner index at the bank-level. The conditional mean and quantile regression estimations use all banks in the sample and monthly data between 2008:M01 and 2019:M03. Column (2) shows the estimation using ordinary least squares. Columns (3) to (9) report the quantile regression estimates. We report the traditional R^2 in ordinary regression, while pseudo R^2 are generated for the quantile regression. The F-statistic is used to reject equality of coefficients on the interaction term across all quantiles and also between any two quantiles. The interaction terms measure the joint effect of the financial reform (D_{2t}) for (i) D-SIBs; (ii) other small banks; and (iii) investment banks. We include common macroeconomic controls and bank-level controls based on the literature. All continuous variables are measured using annual changes. All quantile regression specifications were estimated using STATA's command "sqreg" with bootstrap standard errors. The number of replications used to obtain the estimate of the variance-covariance matrix of the estimators (standard errors) was 20. All in all, we used 3,902 observations in the estimations.

Table A17: Markov switching regime specifications

Variables	PCA		Standard Lerner		Refined Lerner		Boone
	Mean	Median	Mean	Median	Mean	Median	
α_1	0.9323*** (0.1996)	-1.3162*** (0.1307)	-0.0155*** (0.0017)	-0.0098*** (0.0031)	-0.0109*** (0.0013)	-0.0081*** (0.0012)	-0.0364*** (0.0051)
α_2	1.0440*** (0.2028)	0.5850*** (0.1126)	0.0181*** (0.0018)	0.0203*** (0.0029)	0.0051** (0.0008)	0.0079*** (0.0014)	0.0181*** (0.0039)
σ_1	0.7807*** (0.0910)	0.4511*** (0.0968)	0.0088*** (0.0011)	0.0088*** (0.0023)	0.0058*** (0.0006)	0.0064*** (0.0006)	0.0128*** (0.0037)
σ_2	0.7625*** (0.0834)	0.8255*** (0.0625)	0.0133*** (0.0014)	0.0124*** (0.0011)	0.0052*** (0.0004)	0.0047*** (0.0007)	0.0211*** (0.0018)
$p_{1,1}$	0.9374*** (0.0323)	0.9346*** (0.0285)	0.9510*** (0.0270)	0.9264*** (0.0531)	0.9191*** (0.0277)	0.9470*** (0.0201)	0.9120*** (0.0420)
$p_{2,1}$	0.0650*** (0.0280)	0.0234*** (0.0122)	0.0380*** (0.0173)	0.0731*** (0.0266)	0.0379*** (0.0185)	0.0879*** (0.0300)	0.0688*** (0.0273)
Obs	111	111	121	121	121	121	111

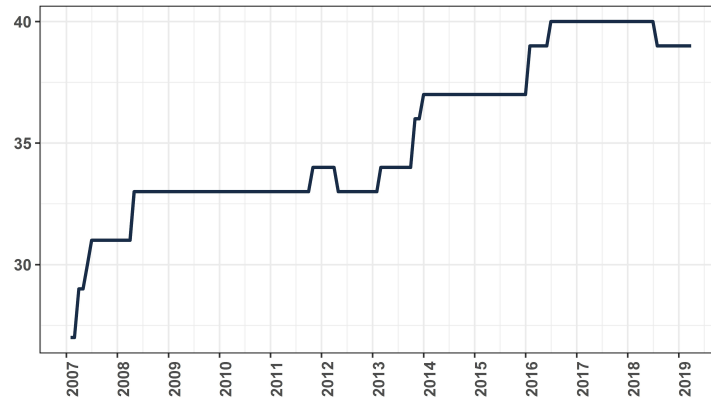
Source: Banco de México, authors' calculations.
 Notes: *** (***) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the Markov switching model estimates for the competition measures. All estimations were done in Stata using the command 'mswitch' which is used for Markov regime switching estimations. All estimations are based on eq.(20). All the specifications were estimated using robust standard errors.

Figure A1: Bank's market share grouped by bank type using total assets, total private non-financial loan portfolio and total deposits.



Source: Banco de México, authors' calculations.
 Notes: This figure shows bank's market shares grouped by bank type using total assets, total private non-financial loan portfolio and total deposits for the period January 2007 to March 2019.

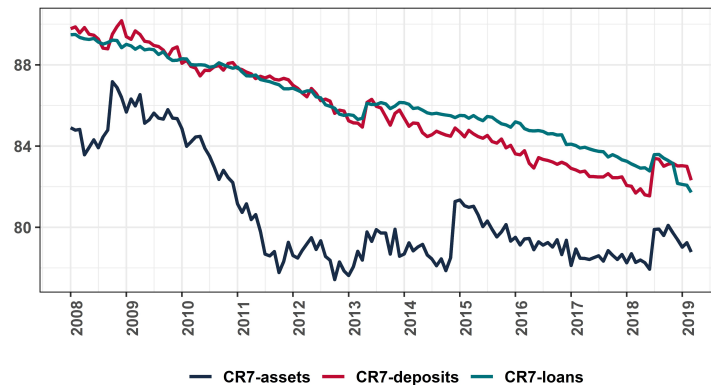
Figure A2: Evolution of the number of banks.



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the number of banks in our sample for the period January 2007 to March 2019.

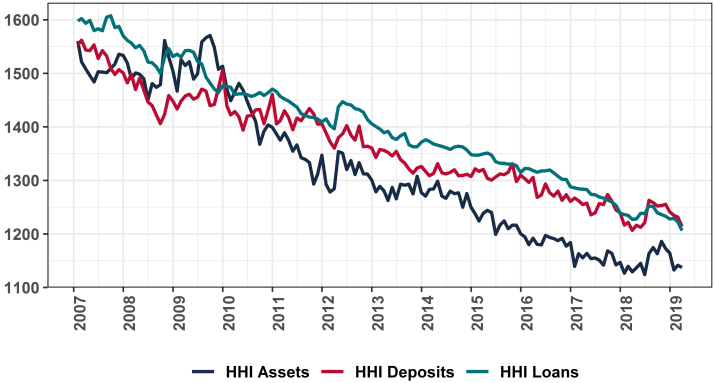
Figure A3: Concentration Ratio (CR_7) for banks total assets, total private non-financial loan portfolio and total deposits.



Source: Banco de México, authors' calculations.

Notes: This figure shows the Concentration Ratio (i.e., CR_7) for total assets, total private non-financial loan portfolio and total deposits for the period January 2008 to March 2019.

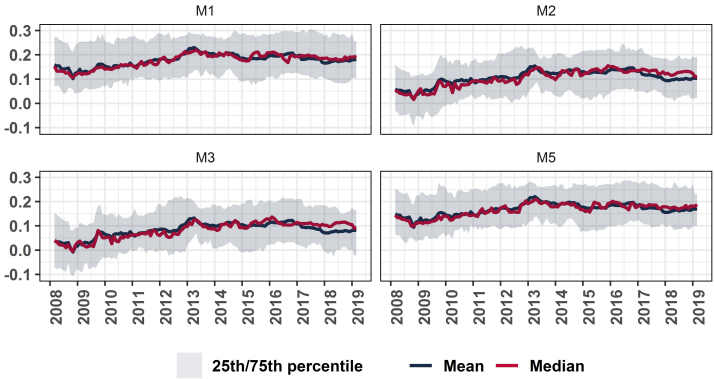
Figure A4: Herfindahl-Hirschman Index (*HHI*) for banks total assets, total private non-financial loan portfolio and total deposits.



Source: Banco de México, authors' calculations.

Notes: This figure shows the Herfindahl-Hirschman index (*HHI*) for total assets, total private non-financial loan portfolio and total deposits for the period January 2007 to March 2019. An increase of the *HHI* index indicates an increase in concentration. Mexican competition authorities deem an industry as concentrated if it has a *HHI* above 2,000. This threshold level is not broadly used in other jurisdictions and its adequacy should be documented and discussed at the international level.

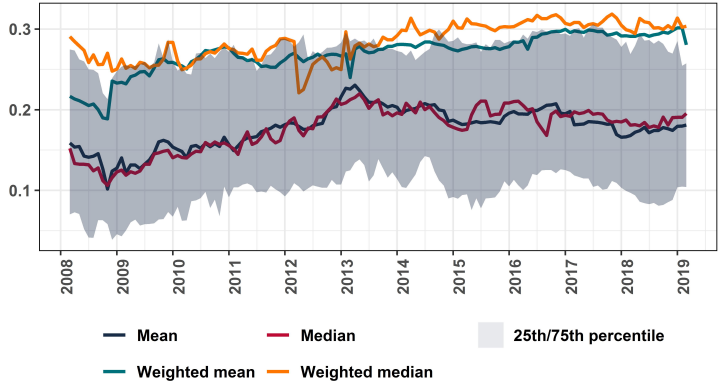
Figure A5: Evolution of the unweighted average of the standard Lerner index of the Mexican banking sector for different specifications



Source: Banco de México, authors' calculations.

Notes: This figure shows the monthly evolution of the unweighted standard Lerner index for the Mexican banking sector in the period January 2008 to March 2019. Each line shows the unweighted average of the Lerner index for four out of the five models estimated in Appendix A Table A2. We omit model M4 because it overlaps with model M1 as the only difference between them is the estimator used to compute the standard errors of the cost function parameters.

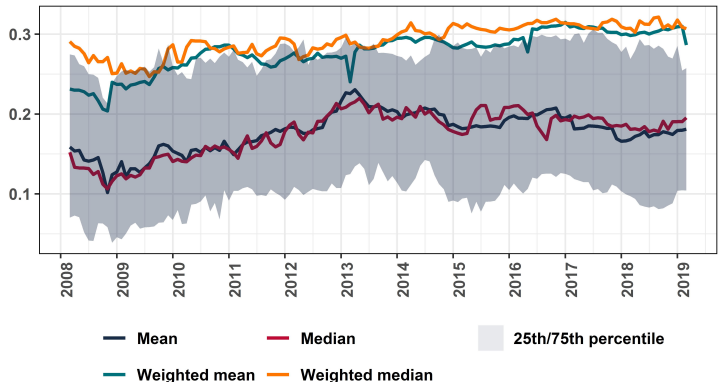
Figure A6: Evolution of the asset-weighted and unweighted average of the standard Lerner index of the Mexican banking sector



Source: Banco de México, authors’ calculations.

Note: This figure shows the monthly evolution of the weighted and unweighted standard Lerner index for the Mexican banking sector in the period January 2008 to March 2019. These Lerner indices are computed using the estimates of our baseline model M1 (see Appendix A Table A2). The weighted average of the Lerner index is computed as described in eq.(4). The weighted median is the median value for each point in time of the bank’s weighted Lerner index. We use bank’s total asset as weight. The shaded area shows the interval between the 25th and 75th percentile of the distribution. As expected, the weighted average has a higher level compared to the unweighted average as D-SIBs have more market power than non-DSIBs (i.e. small banks).

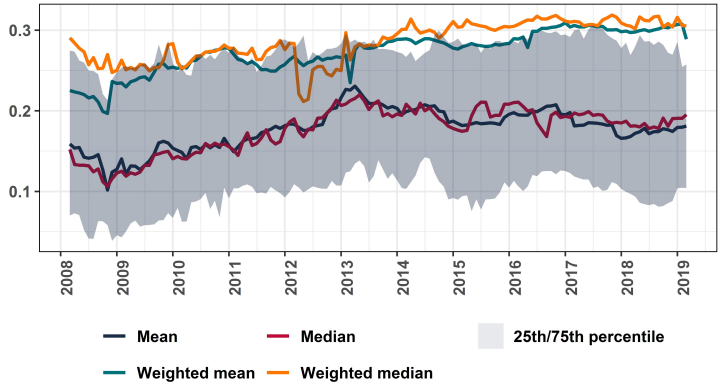
Figure A7: Evolution of the loan-weighted and unweighted average of the standard Lerner index for the Mexican banking sector



Source: Banco de México, authors’ calculations.

Note: This figure shows the monthly evolution of the weighted and unweighted standard Lerner index for the Mexican banking sector in the period January 2008 to March 2019. These Lerner indices are computed using the estimates of our baseline model M1 (see Appendix A Table A2). The weighted average of the Lerner index is computed as described in eq.(4). The weighted median is the median value for each point in time of the bank’s weighted Lerner index. We use each bank’s loan portfolio size as weight. The shaded area shows the interval between the 25th and 75th percentile of the distribution. As expected, the weighted average has a higher level compared to the unweighted average as D-SIBs have more market power than non-DSIBs (i.e. small banks).

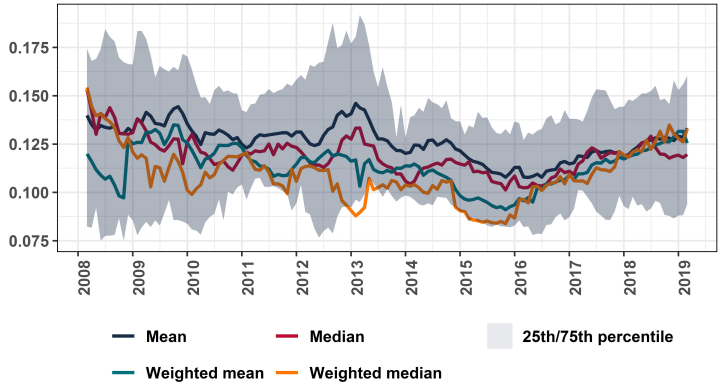
Figure A8: Evolution of the deposit-weighted and unweighted average of the standard Lerner index for the Mexican banking sector



Source: Banco de México, authors’ calculations.

Note: This figure shows the monthly evolution of the weighted and unweighted standard Lerner index for the Mexican banking sector in the period January 2008 to March 2019. These Lerner indices are computed using the estimates of our baseline model M1 (see Appendix A Table A2). The weighted average of the Lerner index is computed as described in eq.(4).The weighted median is the median value for each point in time of the bank’s weighted Lerner index. We use each bank’s deposit share as weight. The shaded area shows the interval between the 25th and 75th percentile of the distribution. As expected, the weighted average has a higher level compared to the unweighted average as D-SIBs have more market power than non-DSIBs (i.e. small banks).

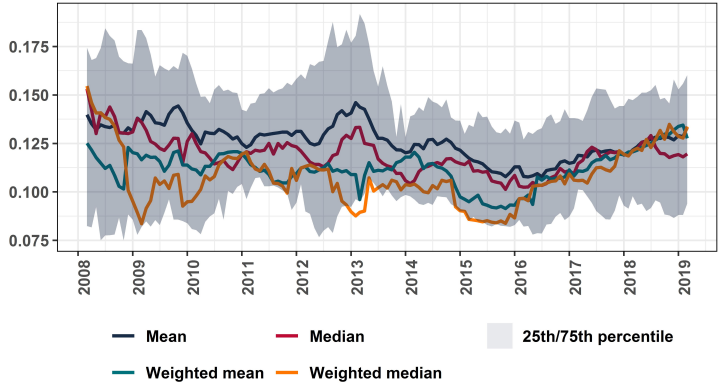
Figure A9: Evolution of the asset-weighted and unweighted average of the refined Lerner index for the Mexican banking sector



Source: Banco de México, authors’ calculations.

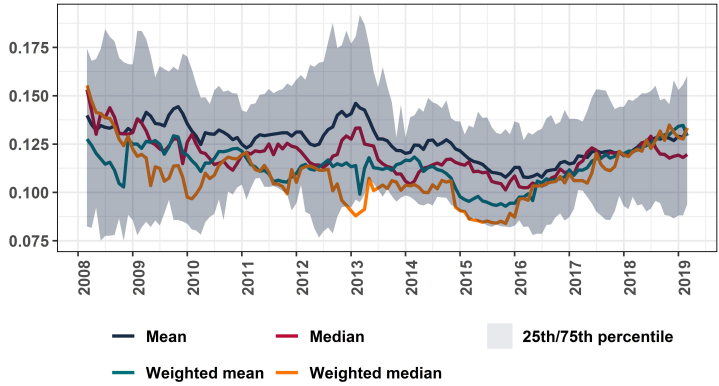
Note: This figure shows the monthly evolution of the asset-weighted and unweighted refined Lerner index for the Mexican banking sector in the period January 2008 to March 2019. These Lerner indices are computed using the stochastic frontier approach. The weighted average of the Lerner index is computed as described in eq.(4).The weighted median is the median value for each point in time of the bank’s weighted Lerner index. We use each bank’s assets share as weight. The shaded area shows the interval between the 25th and 75th percentile of the distribution. In contrast to the standard Lerner index, the weighted average of the mean (median) of the refined Lerner index is almost always smaller in relation to the unweighted counterpart. This suggests that if we adjust D-SIBs bank’s market power by its efficiency, then these banks not always have a lower market power.

Figure A10: Evolution of the loan-weighted and unweighted average of the refined Lerner index for the Mexican banking sector



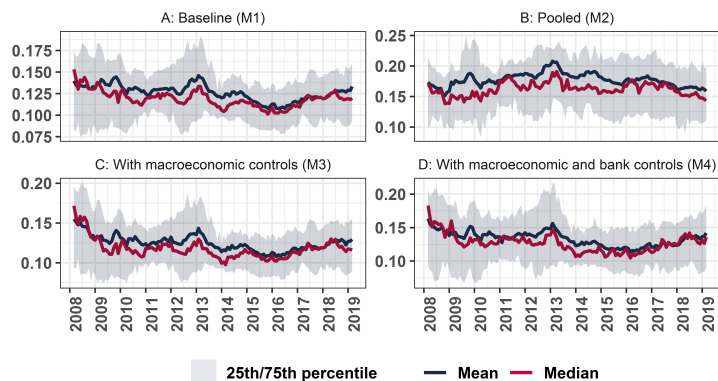
Source: Banco de México, authors’ calculations.
Note: This figure shows the monthly evolution of the loan-weighted and unweighted refined Lerner index for the Mexican banking sector in the period January 2008 to March 2019. These Lerner indices are computed using the stochastic frontier approach. The weighted average of the Lerner index is computed as described in eq.(4).The weighted median is the median value for each point in time of the bank’s weighted Lerner index. We use each bank’s loan share as weight. The shaded area shows the interval between the 25th and 75th percentile of the distribution. In contrast to the standard Lerner index, the weighted average of the mean (median) of the refined Lerner index is almost always smaller in relation to the unweighted counterpart. This suggests that if we adjust D-SIBs bank’s market power by its efficiency, then these banks not always have a lower market power.

Figure A11: Evolution of the deposit-weighted and unweighted average of the refined Lerner index for the Mexican banking sector



Source: Banco de México, authors’ calculations.
Note: This figure shows the monthly evolution of the deposit-weighted and unweighted Lerner index for the Mexican banking sector in the period January 2008 to March 2019. These Lerner indices are computed using the stochastic frontier approach. The weighted average of the Lerner index is computed as described in eq.(4).The weighted median is the median value for each point in time of the bank’s weighted Lerner index. We use each bank’s deposit share as weight. The shaded area shows the interval between the 25th and 75th percentile of the distribution. In contrast to the standard Lerner index, the weighted average of the mean (median) of the refined Lerner index is almost always smaller in relation to the unweighted counterpart. This suggests that if we adjust D-SIBs bank’s market power by its efficiency, then these banks not always have a lower market power.

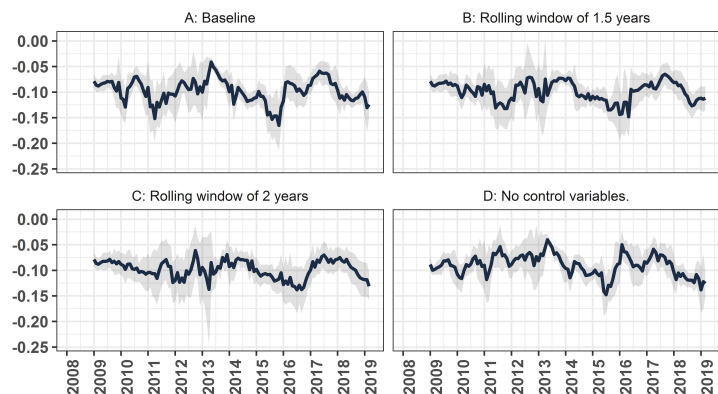
Figure A12: Evolution of the refined Lerner index for different specifications



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the refined Lerner index for each month in the period January 2008 to March 2019 for four different model specifications. The estimation output for each model is fully described in Appendix A Table A3. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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. Panel A shows the baseline model (i.e. M1). Panel B shows M1 estimated with a pooled regression technique (i.e. M2). Panel C is M1 with macroeconomic controls (i.e. M3). Panel D is M3 with bank specific controls (i.e. M4).

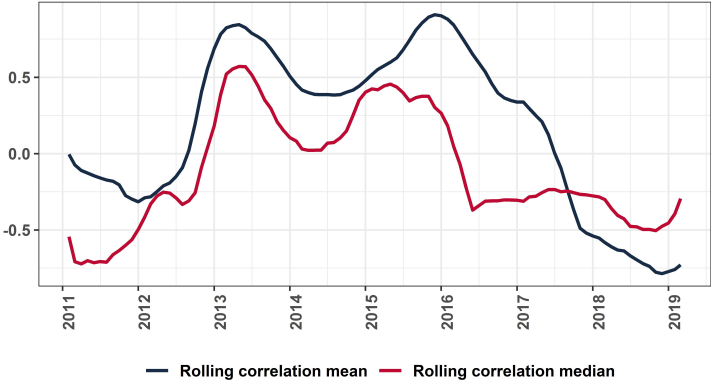
Figure A13: Evolution of the Boone indicator for different specifications



Source: Banco de México, authors' calculations.

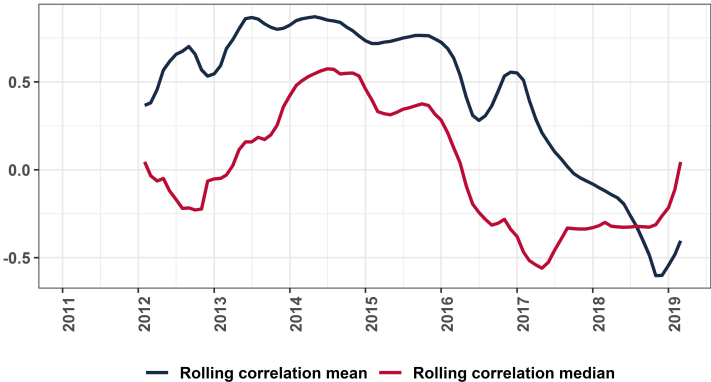
Notes: This figure shows the monthly evolution of the Boone indicator for the Mexican banking sector in the period January 2008 to March 2019. Panel A shows our baseline specification for the Boone indicator where we use a rolling window of 1 year for estimation purposes. Panel B shows the Boone indicator using a rolling window of 1.5 years. Panel C shows the Boone using a rolling window of 2 years. Panel D analyzes what happens when we exclude control variables. All models were estimated using bank and time fixed effects with clustered standard errors.

Figure A14: 36-month rolling window correlation between the mean and median of the standard and refined Lerner index



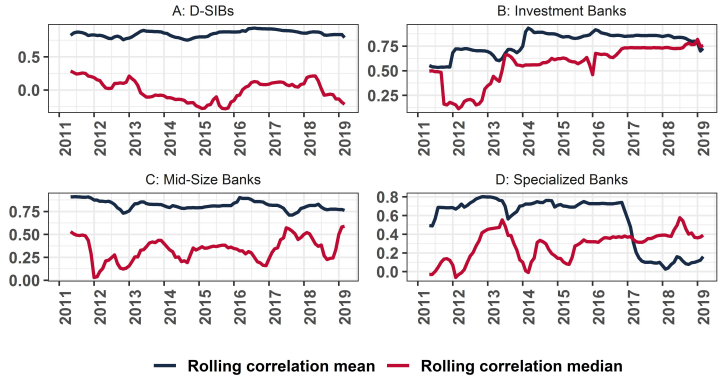
Source: Banco de México, authors' calculations.
Notes: This figure shows the 36-month rolling window correlation between the mean (median) standard and refined Lerner index. The plotting range is restricted and initiates until 2011 because we lose the first three years of data to attain a reliable estimate.

Figure A15: 36-month rolling window correlation between the YoY (year on year) change in mean and median between the standard and the refined Lerner index.



Source: Banco de México, authors' calculations.
Notes: This figure shows the 36-month rolling window correlation between the YoY change in mean and median between the standard and the refined Lerner index. We lose the first three-years of data due to the fact that a reliable estimate is obtained until 2012. To compute this correlation, we compute the YoY change in the mean and median of the standard and refined Lerner index. Then we compute the correlation between the mean (median) of the standard and refined Lerner index. A negative correlation suggests that these two measures show an opposing view on market power and competition performance.

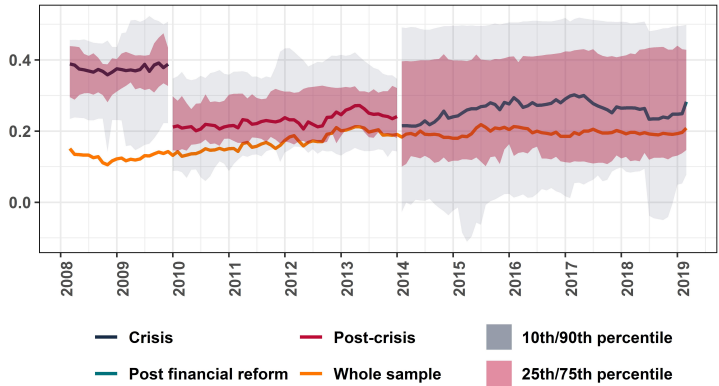
Figure A16: 36-month rolling correlation between the YoY (year on year) change in mean and median between the standard and the refined Lerner index grouped by bank business type.



Source: Banco de México, authors' calculations.

Notes: This figure shows the 36-month rolling window correlation between the YoY change in mean and median between the standard and the refined Lerner index grouped by bank type. We lose the first three-years of data due to the fact that a reliable estimate is obtained until 2012. To compute this correlation, we start by computing the YoY change in the mean and median of the standard and refined Lerner index by bank type. Then we compute the correlation between the mean (median) of the standard and refined Lerner index by bank type. A negative correlation suggests that these two measures show an opposing view on market power and competition performance. Panel A shows the correlation between D-SIBs. Panel B shows the correlation between investment banks. Panel C shows the correlation between mid-size banks. Panel D shows the correlation between specialized banks.

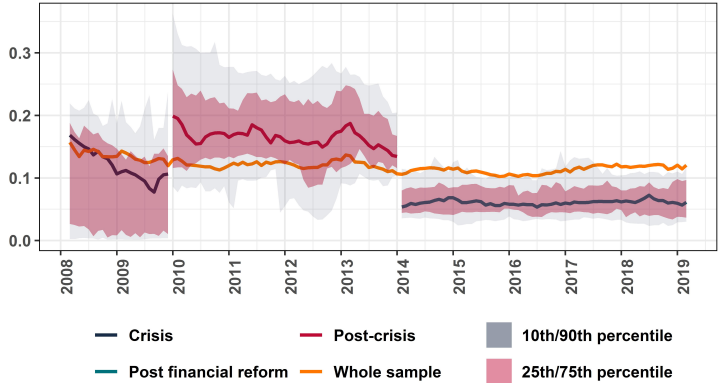
Figure A17: Evolution of the unweighted standard Lerner index for three time periods: crisis (2008-2009), post-crisis (2010-2013), post-financial reform (2014-2019)



Source: Banco de México, authors' calculations.

Notes: This figure shows the monthly evolution of the standard Lerner index during January 2008 to March 2019 using three different sub-samples. The solid orange line is the median of the standard Lerner index for the full sample. The solid purple, red and blue lines are the median of the standard Lerner index for each sub-sample. The pink shaded area marked as '25th/75th percentile' shows the interval between the 25th and 75th percentile of the distribution in each sub-sample, while the light grey shaded area marked as '10th/90th percentile' shows the interval between the 10th and 90th 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.

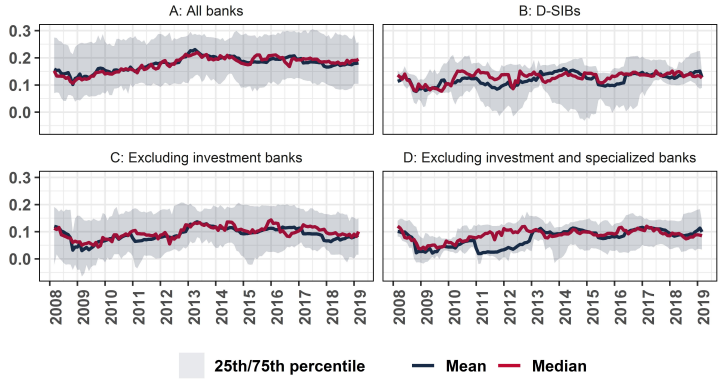
Figure A18: Evolution of the unweighted refined Lerner index for the three time periods: crisis (2008-2009), post-crisis (2010-2013), post-financial reform (2014-2019)



Source: Banco de México, authors’ calculations.

Notes: This figure shows the monthly evolution of the refined Lerner index during January 2008 to March 2019 using three different sub-samples. The solid orange line is the median of the refined Lerner index for the full sample. The solid purple, red and blue lines are the median of the refined Lerner index for each sub-sample. The pink shaded area marked as ‘25th/75th percentile’ shows the interval between the 25th and 75th percentile of the distribution in each sub-sample, while the light grey shaded area marked as ‘10th/90th percentile’ shows the interval between the 10th and 90th 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.

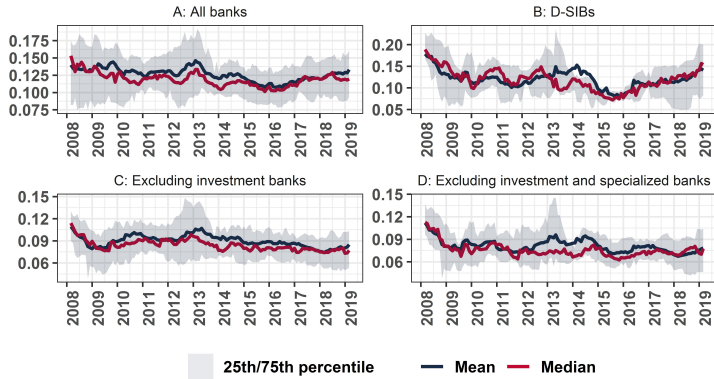
Figure A19: Evolution of the unweighted Lerner index based on the standard estimation approach for different banking groups



Source: Banco de México, authors’ calculations.

Notes: This figure shows the evolution of the Lerner index based on the standard approach for each month in the period January 2008 to March 2019 estimated for different banking groups. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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 A20: Evolution of the unweighted Lerner index based on the refined estimation approach for different banking groups



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the Lerner index based on the refined approach for each month in the period January 2008 to March 2019 estimated for different banking groups. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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.

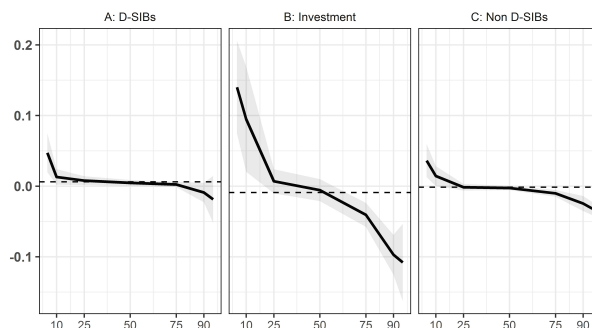
Figure A21: Evolution of the composite competition indices over the sample period



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the composite competition indices measured in annual difference using principal components analysis. The 'Mean' line refers to the composite index constructed using the mean value of the standard and refined Lerner indices as well as the Boone indicator, while the 'Median' line refers to the composite index constructed using the median value of the standard and Refined Lerner indices and the Boone indicator. The sample period starts in 2010 because it takes one year (i.e., 2008) to compute the first value of the Boone indicator due to sample restrictions, and another year (i.e., 2009) to compute its annual variation. An increase in the composite index is a sign of deterioration in competition. The labels on the horizontal axis indicate the beginning of the year.

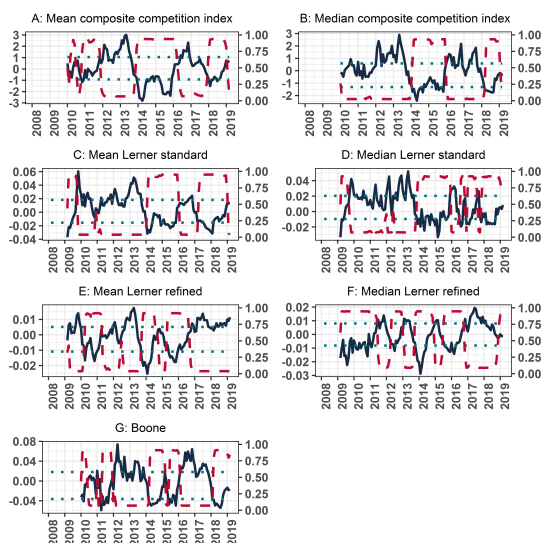
Figure A22: Marginal effect of the financial reform per bank type on quantiles of the refined Lerner index



Source: Banco de México, authors' calculations.

Notes: Each panel shows the value of the estimated interaction coefficients per bank type (vertical axis) for varying quantiles of the market power measure based on the refined Lerner index (horizontal axis). The solid line shows the transition of the interaction terms coefficient's estimate while the shaded area represents the 95% confidence interval using bootstrap standard errors. The dotted line represents the conditional mean estimate (OLS estimation) of the interaction term and this line is independent of the quantiles of the market power.

Figure A23: Markov switching model for the composite competition measures



Source: Banco de México, authors' calculations.

Notes: This figure shows evolution of the composite competition indices and the twelve month difference of each competition measure (dark blue solid line), the conditional means of each competition regime (green dot line) and the probability of a high competition regime (red dashed line). Panel A and B show the mean and the median of the composite competition indices. Panel C and D show the mean and median of the annual change of the standard Lerner index, respectively. Panel E and F show the mean and median of the annual change of the refined Lerner index, respectively. Panel G shows the annual change of the Boone indicator. The left vertical axis measures the value of the twelve month difference in the competition measure. In Panel A and B we use the first principal component based on the annual difference of our three NEIO competition measures. The right vertical axis measures the probability of a high or intense competition regime. The labels on the horizontal axis indicate the end of the year.

Appendix B: Using Quarterly Data as a Robustness Check

In this section, we document the empirical analysis that shows that using quarterly data does not change or modify any of our results as the level, trend or pattern and variability of all non-structural indicators analyzed in this study (i.e. Lerner index, Panzar and Rosse, and Boone) remain broadly the same. In other words, results are qualitatively similar. As we discussed in the introduction of this study, using higher frequency data such as monthly observations offers a number of advantages. As an example, uncovered impacts attributable to either market or idiosyncratic bank shocks may not be clearly identified with quarterly data.

The variable definitions used for this exercise are the same as the ones presented in Appendix A. In Table B1 we present the descriptive statistics of the variables used in this exercise. As expected, quarterly information has less variability. Next, we focus on the standard Lerner index. Table B2 shows the results for the standard Lerner index for different specifications. Figure B1 shows the evolution of the unweighted Lerner index distribution while Figure B2 shows the same unweighted Lerner index distribution grouped by bank type.¹⁰¹ Then, we present the results for the refined Lerner index distribution. Table B3 shows the estimation result for different specifications of the refined Lerner index, while Figure B3 and Figure B4 show its evolution during the period of our study for all banks and also for the banks grouped by its type, respectively. Table B4 and Table B5 show the estimates for different specifications of the Panzar-Rosse H -statistic. Figure B5 shows the evolution of the Boone indicator. Finally, Table B6 shows the correlation matrix between both structural and non-structural competition indicators.

¹⁰¹Following the paper, we identified four bank groups: D-SIBs, Investment banks, Mid-size banks and Specialized banks.

Table B1: Descriptive statistics of micro and macro variables, quarterly data, for the period 2008:Q1 to 2019:Q1

Variable	Mean	Std Dev	Min.	Q. 25	Median	Q. 75	Max
Dependent variables							
Total costs (C_{it})	16.00	28.95	0.13	1.21	3.81	13.41	173.82
Revenues to costs ratio (RC_{it})	1.16	0.23	0.32	1.04	1.12	1.23	2.85
Total revenues (TR_{it})	19.12	35.40	0.06	1.44	4.48	15.53	238.59
Return on assets ^c (ROA_{it})	0.01	0.03	-0.19	0.00	0.01	0.02	0.24
Profits to assets ratio (π_{it})	0.02	0.04	-0.29	0.00	0.01	0.02	0.35
Independent variables							
<i>Input prices</i>							
Bank funding costs ($W_{it}^{(1)}$)	0.04	0.03	0.00	0.02	0.03	0.05	0.40
Bank labor expenses ($W_{it}^{(2)}$)	0.03	0.05	0.00	0.00	0.01	0.02	0.43
Operational costs ($W_{it}^{(3)}$)	0.05	0.07	0.00	0.01	0.02	0.04	0.43
<i>Other bank-level variables</i>							
Total assets (Q_{it})	177.09	343.92	0.34	14.52	34.39	114.98	2035.34
Revenues to assets ratio (P_{it})	0.15	0.14	0.02	0.08	0.11	0.15	0.75
Costs to revenues ratio (\hat{C}_{it})	0.89	0.18	0.36	0.81	0.89	0.97	3.15
Provisions to assets ratio (PR_{it}/Q_{it})	0.02	0.03	0.00	0.01	0.02	0.03	0.17
Loans to assets ratio (L_{it}/Q_{it})	0.39	0.25	0.00	0.18	0.37	0.58	0.94
Retail funding to liabilities ratio (RF_{it}/LR_{it})	0.50	0.27	0.00	0.29	0.54	0.70	0.99
Average risk weight (ARW_{it})	0.68	0.32	0.16	0.45	0.63	0.82	2.13
<i>Macroeconomic variables</i>							
Economic activity index YoY (EAI_{it})	0.02	0.03	-0.08	0.02	0.02	0.03	0.07
Unemployment rate (UR_{it})	0.04	0.01	0.03	0.04	0.04	0.05	0.06
Inflation rate (IR_{it})	0.04	0.01	0.02	0.03	0.04	0.05	0.07

Source: Banco de México, authors' calculations.

Notes: This table reports quarterly descriptive statistics of all micro and macro variables by mean, standard deviation, minimum, 25th percentile (i.e. Q.25) or first quartile, median, 75th percentile (i.e. Q.75) or third quartile and maximum for analysis period 2008:Q1 to 2019:Q1. All variables are unit free except total costs, total revenue and total assets which are reported in thousands of millions (i.e. in B or 10^9 or 'one thousand million' in North America) in Mexican pesos (i.e. MXN). There are 43 banks in total and 7 out of 43 banks are D-SIBs, 5 out of 43 are investment banks, 15 out of 43 are mid-sized banks, and 14 out of 43 are specialized banks.

Table B2: Multivariate linearly constrained panel regression analysis for standard Lerner index with quarterly data

VARIABLES	M1	M2	M3	M4	M5
$\log(Q_{it})$	1.1090*** (0.2085)	0.8420*** (0.1945)	0.9314*** (0.1455)	1.1090*** (0.0541)	1.0458*** (0.1403)
$\log(Q_{it})^2$	-0.0097 (0.0126)	0.0052 (0.0087)	0.0023 (0.0070)	-0.0097*** (0.0030)	-0.0061 (0.0073)
$\log(W_{it}^{(1)})$	0.3155*** (0.0856)	-0.2239 (0.2020)	-0.0820 (0.1452)	0.3155*** (0.0320)	0.3264*** (0.0853)
$\log(W_{it}^{(2)})$	0.2190 (0.1468)	0.4561*** (0.1212)	0.4072*** (0.0994)	0.2190*** (0.0357)	0.2061 (0.1412)
$\log(W_{it}^{(3)})$	0.4655*** (0.1342)	0.7678*** (0.2423)	0.6749*** (0.1606)	0.4655*** (0.0374)	0.4675*** (0.1363)
$\log(Q_{it})\log(W_{it}^{(1)})$	0.0213** (0.0098)	0.0590*** (0.0171)	0.0535*** (0.0132)	0.0213*** (0.0029)	0.0204*** (0.0077)
$\log(Q_{it})\log(W_{it}^{(2)})$	-0.0216 (0.0171)	-0.0441*** (0.0129)	-0.0461*** (0.0123)	-0.0216*** (0.0038)	-0.0204 (0.0167)
$\log(Q_{it})\log(W_{it}^{(3)})$	0.0003 (0.0140)	-0.0150 (0.0224)	-0.0075 (0.0153)	0.0003 (0.0038)	0.0000 (0.0148)
$\log(W_{it}^{(1)})^2$	0.0514*** (0.0148)	0.0018 (0.0218)	0.0243 (0.0168)	0.0514*** (0.0024)	0.0519*** (0.0152)
$\log(W_{it}^{(2)})^2$	-0.0112 (0.0137)	-0.0182 (0.0164)	-0.0242 (0.0188)	-0.0112*** (0.0022)	-0.0116 (0.0151)
$\log(W_{it}^{(3)})^2$	0.0175 (0.0136)	0.0438*** (0.0134)	0.0370*** (0.0124)	0.0175*** (0.0026)	0.0161 (0.0139)
$\log(W_{it}^{(1)})\log(W_{it}^{(2)})$	-0.0113 (0.0103)	0.0301*** (0.0103)	0.0185* (0.0094)	-0.0113*** (0.0021)	-0.0121 (0.0105)
$\log(W_{it}^{(1)})\log(W_{it}^{(3)})$	-0.0400*** (0.0131)	-0.0319* (0.0183)	-0.0428** (0.0167)	-0.0400*** (0.0022)	-0.0398*** (0.0140)
$\log(W_{it}^{(2)})\log(W_{it}^{(3)})$	0.0225 (0.0168)	-0.0119 (0.0206)	0.0058 (0.0196)	0.0225*** (0.0025)	0.0236 (0.0177)
Bank FE	Yes	No	No	Yes	Yes
Time FE	Yes	No	No	Yes	No
Bank type dummies	No	No	Yes	No	No
<i>Inflation rate (YoY)</i>					0.6691 (0.6828)
<i>Econ. activity index (YoY)</i>					-0.3713 (0.2437)
<i>Unemployment rate</i>					-0.7103 (1.2862)
<i>Constant</i>		2.2763** (0.9881)			

Source: Banco de México, authors' calculations.

Notes: *** (***) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the multivariate estimates for the standard Lerner index for the five models (i.e. M1 to M5) under analysis. Model M1 and M5 were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. All estimations were done in Stata using the command 'cnreg' which is used for constrained linear panel regressions along with different options available in the software as discussed in section 4.2. All estimations are based on eq.(2). We have an unbalanced panel of 1,443 bank-quarter observations that cover the period from 2008:Q1 to 2019:Q1. Time fixed effects were introduced to control for heterogeneity for each quarter. Bank type fixed effects were introduced to take into account heterogeneity across four different bank business models.

Table B3: Estimations for the Refined Lerner index, quarterly data, for the period 2008:Q1 to 2019:Q1

VARIABLES	M1	M2	M3	M4	M5
$\log(Q_{it})$	0.0887 (0.0632)	0.0356*** (0.0085)	0.0888 (0.0670)	0.0762 (0.0643)	0.0887*** (0.0141)
$\log(W_{it}^{(1)}/W_{it}^{(3)})$	-0.0594 (0.0447)	0.0038 (0.0144)	-0.0568 (0.0478)	-0.0519 (0.0383)	-0.0594*** (0.0076)
$\log(W_{it}^{(2)}/W_{it}^{(3)})$	0.0262 (0.0233)	-0.0207* (0.0112)	0.0267 (0.0229)	0.0306 (0.0198)	0.0262*** (0.0058)
T	-0.0001 (0.0020)	0.0004 (0.0009)	0.0006 (0.0022)	0.0009 (0.0023)	-0.0001 (0.0006)
Provisions to assets				0.0501 (1.0641)	
Loans to assets				0.0351 (0.1671)	
Retail funding to total liabilities				-0.1045 (0.0975)	
Average risk weights				-0.0742 (0.0959)	
Inflation rate (YoY)			0.1103 (0.5633)	0.2311 (0.4717)	
Econ. activity index (YoY)			-0.0539 (0.3563)	0.1390 (0.3165)	
Unemployment rate			1.6968 (1.7867)	0.6926 (1.3948)	
Constant		0.5311*** (0.0909)			
σ^2	0.0532*** (0.0178)	0.0969*** (0.0295)	0.0533*** (0.0179)	0.0569*** (0.0190)	0.0532*** (0.0031)
λ	2.5302*** (0.8263)	3.12*** (0.0549)	2.5643*** (0.8494)	4.9309 (3.8478)	2.5302*** (0.2163)
Bank FE	Yes	No	Yes	Yes	Yes
Observations	1,503	1,503	1,503	1,503	1,503

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the multivariate estimates for the refined Lerner index for the periods under analysis. All estimations were done in Stata using the command 'sftfe' (see Chen et al. (2014) and Belotti and Ilardi (2018)) and 'frontier' which are used for stochastic frontier analysis. All estimations are based on eq.(11). All the specifications with the exception of M5 were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. The parameter λ indicates the share of technical inefficiency in the total error variance, meanwhile σ^2 denotes the total error variance. Model M1 refers to our baseline specification. Model M2 refers to the model estimated with a pooled approach (without fixed effects). Model M3 refers to our baseline specification, including macroeconomic control variable. Model M4 refers to our baseline specification, including macroeconomic and bank-level control variables. Model M5 is the same as our baseline but estimated without clustered standard errors.

Table B4: Panzar-Rosse H Statistic estimations, quarterly data, for the period 2008:Q1 to 2019:Q1

VARIABLES	H	$H - ROA$	H	$H - ROA$
$\log(W_{it}^{(1)})$	0.258** (0.112)	-0.00130 (0.00282)	0.213 (0.131)	-0.00154 (0.00276)
$\log(W_{it}^{(2)})$	-0.0106 (0.0644)	0.00366 (0.00344)	-0.000985 (0.0572)	0.00351 (0.00321)
$\log(W_{it}^{(3)})$	0.0353 (0.169)	-0.00780 (0.00614)	0.0348 (0.138)	-0.00780 (0.00676)
Provisions to assets			6.436** (2.592)	0.0537 (0.221)
Loans to assets			-0.175 (0.443)	0.0169 (0.0229)
Retail funding to total liabilities			0.819** (0.335)	-0.00882 (0.0120)
Average risk weight			-0.476 (0.298)	-0.00394 (0.0120)
R-squared	0.662	0.092	0.708	0.099

Source: Banco de México, authors' calculations.

Notes: *** (**) [*] significant at 1% (5%) [10%] level (two-sided test). This table displays the estimates for the Panzar-Rosse H -Statistic and $H - ROA$ under analysis. All models were estimated using bank and time fixed effects with clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. All estimations were done in Stata using the command 'xtreg' which is used for fixed effects linear panel regressions. All estimations are based on eq.(23). Time fixed effects were introduced to control for heterogeneity for each quarter. Bank fixed effects were introduced to take into account heterogeneity across banks. We have an unbalanced panel of 1,503 bank-quarter observations that cover the period from 2008:Q1 to 2019:Q1.

Table B5: Panzar-Rosse H -Statistic results, quarterly data, for the period 2008:Q1 to 2019:Q1

Model	Statistic	Coeff.	S.E.	Confidence intervals 95%	p-values			
					$H_0: H = 0$	$H_0: H > 0$	$H_0: H < 0$	$H_0: H = 1$
Without control variables	H-statistic	0.2826	0.2594	(-0.2409,0.8062)	0.2821	0.8589	0.1410	0.0084
	H-ROA	-0.0054	0.0054	(-0.0164,0.0055)	0.3243	0.1621	0.8378	0
With control variables	H-statistic	0.2470	0.2322	(-0.2216,0.7158)	0.2935	0.8532	0.1467	0.0023
	H-ROA	-0.0058	0.0064	(-0.0189,0.0072)	0.3747	0.1873	0.8126	0

Source: Banco de México, authors' calculations.

Notes: This table displays the estimates for the Panzar-Rosse H -Statistic and for the $H - ROA$ long run equilibrium test for all models with and without control variables. Moreover, the table also shows the p-values associated to different one-side and two-side alternatives for the H -Statistic. The H -Statistic and the $H - ROA$ were estimated and calculated following eq.(23) and eq.(24). The models were estimated using clustered standard errors grouped by individual banks to attain consistent estimates to any pattern of heteroskedasticity within banks. We have an unbalanced panel of 1,503 bank-quarter observations that cover the period from 2008:Q1 to 2019:Q1. Time fixed effects were introduced to control for heterogeneity for each quarter. Bank type fixed effects were introduced to take into account heterogeneity across four different bank business models.

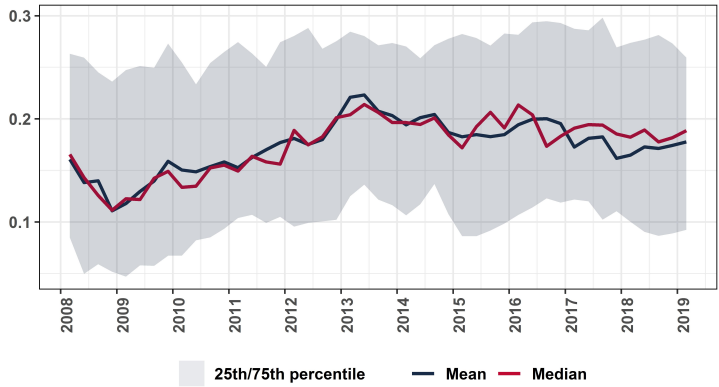
Table B6: Correlation matrix between competition measures, quarterly data

#	Variable	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Number of banks	-0.6 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	-0.9 ^a	0.6 ^a	0.4 ^a	0.8 ^a	0.8 ^a	0.8 ^a	0.8 ^a	0.8 ^a	0.9 ^a	-0.6 ^a	-0.8 ^a	-0.2	-0.3 ^c	0	0	-0.1	-0.1	-0.4 ^b
2	CR ₇ by assets		0.8 ^a	0.8 ^a	0.9 ^a	0.7 ^a	0.8 ^a	-0.8 ^a	-0.8 ^a	-0.5 ^a	-0.6 ^a	-0.7 ^a	-0.6 ^a	-0.5 ^a	-0.6 ^a	0.5 ^a	0.5 ^a	0.3 ^b	0.5 ^a	0.1	0.3 ^c	0.3 ^b	0.4 ^a	0.1
3	CR ₇ by loans			1 ^a	1 ^a	1 ^a	1 ^a	-0.7 ^a	-0.6 ^a	-0.7 ^a	-0.8 ^a	-0.8 ^a	-0.8 ^a	-0.7 ^a	-0.8 ^a	0.6 ^a	0.6 ^a	0.2	0.3 ^c	0	0	0.2	0.2	0.3 ^b
4	CR ₇ by deposits				1 ^a	1 ^a	1 ^a	-0.8 ^a	-0.6 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.8 ^a	-0.7 ^a	-0.8 ^a	0.6 ^a	0.7 ^a	0.3 ^c	0.4 ^a	0.1	0.2	0.3 ^c	0.3 ^c	0.3 ^b
5	HHI Assets					1 ^a	1 ^a	-0.8 ^a	-0.7 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.8 ^a	-0.7 ^a	-0.8 ^a	0.6 ^a	0.7 ^a	0.3 ^c	0.4 ^a	0.1	0.2	0.3 ^c	0.3 ^b	0.3 ^c
6	HHI Deposits						1 ^a	-0.7 ^a	-0.6 ^a	-0.8 ^a	-0.8 ^a	-0.9 ^a	-0.8 ^a	-0.7 ^a	-0.8 ^a	0.6 ^a	0.7 ^a	0.2	0.3 ^b	0	0.1	0.2	0.2	0.4 ^b
7	HHI Loans							-0.7 ^a	-0.6 ^a	-0.8 ^a	-0.8 ^a	-0.8 ^a	-0.8 ^a	-0.7 ^a	-0.9 ^a	0.6 ^a	0.7 ^a	0.2	0.3 ^c	0	0	0.2	0.2	0.4 ^b
8	Median Lerner Standard (MLS)								0.9 ^a	0.6 ^a	0.5 ^a	0.7 ^a	0.5 ^a	0.5 ^a	0.5 ^a	-0.5 ^a	-0.5 ^a	-0.4 ^a	-0.6 ^a	-0.2	-0.4 ^b	-0.4 ^a	-0.5 ^a	0
9	Mean Lerner Standard (mls)									0.5 ^a	0.4 ^a	0.6 ^a	0.5 ^a	0.4 ^a	0.4 ^a	-0.5 ^a	-0.4 ^b	-0.5 ^a	-0.6 ^a	-0.3 ^b	-0.4 ^a	-0.5 ^a	-0.5 ^a	0.1
10	Weighted MLS by assets										0.7 ^a	0.9 ^a	0.8 ^a	1 ^a	0.8 ^a	-0.6 ^a	-0.7 ^a	-0.2	-0.4 ^b	0	-0.1	-0.2	-0.2	-0.4 ^a
11	Weighted mls by assets											0.7 ^a	1 ^a	0.7 ^a	1 ^a	-0.7 ^a	-0.6 ^a	-0.2	0	-0.1	0.1	-0.2	0	-0.2
12	Weighted MLS by loans												0.7 ^a	0.8 ^a	0.7 ^a	-0.6 ^a	-0.7 ^a	-0.2	-0.5 ^a	0	-0.2	-0.2	-0.3 ^b	-0.3 ^b
13	Weighted mls by loans													0.8 ^a	1 ^a	-0.7 ^a	-0.6 ^a	-0.1	0	0	0.2	-0.1	0.1	-0.2
14	Weighted MLS by deposits														0.8 ^a	-0.5 ^a	-0.7 ^a	-0.1	-0.3 ^c	0	0	-0.1	-0.1	-0.4 ^a
15	Weighted mls by deposits															-0.7 ^a	-0.7 ^a	-0.1	0	0	0.2	-0.1	0.1	-0.2
16	Median Lerner Refined (MLR)																0.8 ^a	0.6 ^a	0.5 ^a	0.4 ^a	0.4 ^b	0.5 ^a	0.5 ^a	0.2
17	Mean Lerner Refined (mlr)																	0.4 ^a	0.6 ^a	0.3 ^c	0.4 ^a	0.4 ^a	0.5 ^a	0.3 ^b
18	Weighted MLR by assets																		0.6 ^a	0.9 ^a	0.8 ^a	1 ^a	0.8 ^a	-0.1
19	Weighted mlr by assets																			0.5 ^a	0.9 ^a	0.6 ^a	0.9 ^a	0.1
20	Weighted MLR by loans																					0.7 ^a	0.9 ^a	0.7 ^a
21	Weighted mlr by loans																						0.8 ^a	1 ^a
22	Weighted MLR by deposits																							0.8 ^a
23	Weighted mlr by deposits																							
24	Boone indicator																							0

Source: Banco de México, authors' calculations.

Notes: a (b) [c] significant at 1% (5%) [10%] level. This table displays the pairwise Pearson correlation matrix between both structural and non-structural competition measures and its statistical significance as well as the hypothesis test that Pearson correlation coefficient is zero.

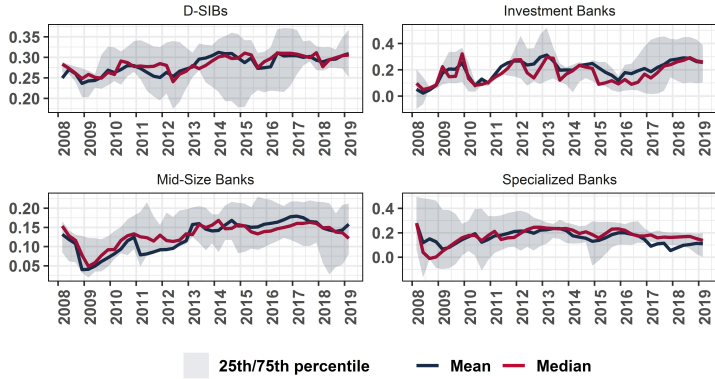
Figure B1: The evolution of the unweighted Lerner index distribution based on the standard approach, quarterly data, for the period 2008:Q1 to 2019:Q1



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the Lerner index for each quarter in the period 2008:Q1 to 2019:Q3. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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.

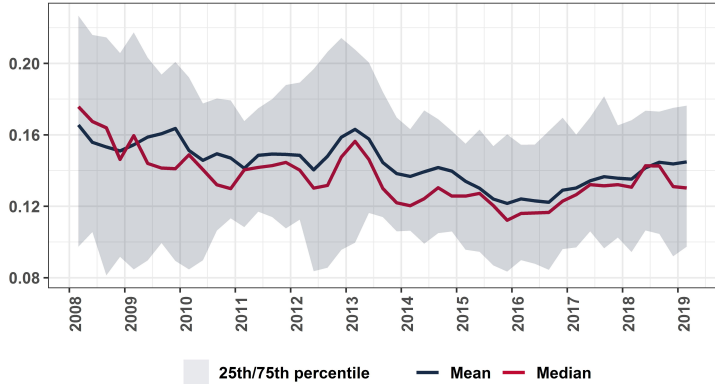
Figure B2: The evolution of the unweighted Lerner index distribution by bank type based on the standard approach, quarterly data, for the period from 2008:Q1 to 2019:Q1



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the Lerner index grouped by bank type for each quarter in the period 2008:Q1 to 2019:Q1. Panel A shows the evolution for D-SIBs; Panel B shows the evolution for investment banks; Panel C shows the evolution for mid-size banks; and Panel D: shows the evolution for specialized banks. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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.

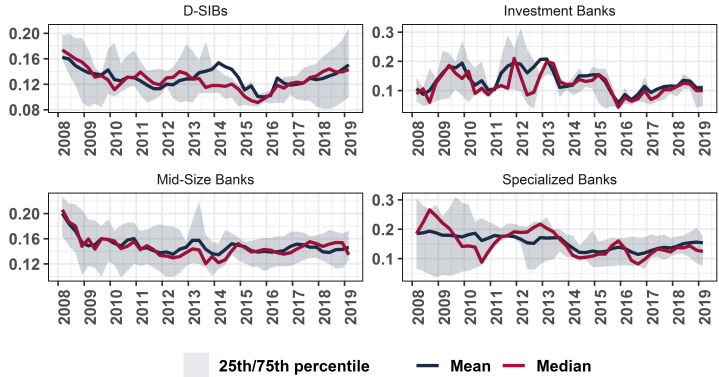
Figure B3: The evolution of the unweighted Lerner index distribution based on the refined approach, quarterly data, for the period 2008:Q1 to 2019:Q1



Source: Banco de México, authors' calculations.

Notes: This figure shows the evolution of the Lerner index for each quarter in the period 2008:Q1 to 2019:Q1. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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.

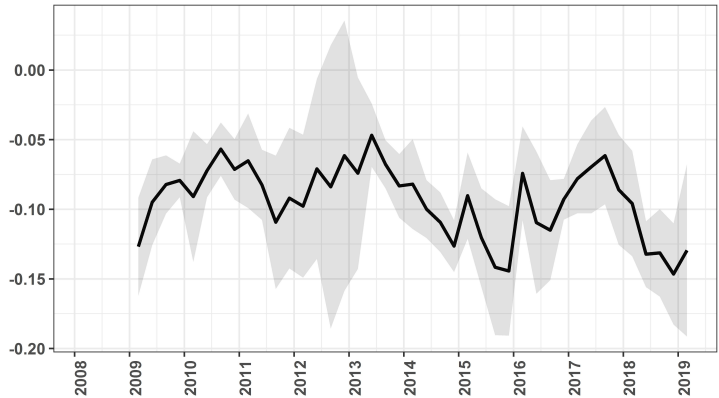
Figure B4: The evolution of the unweighted Lerner index distribution by bank type based on the refined approach, quarterly data, for the period 2008:Q1 to 2019:Q1



Source: Banco de México, authors’ calculations.

Notes: This figure shows how the Lerner index distribution has evolved for different banking groups. Panel A shows the evolution for D-SIBs; Panel B shows the evolution for investment banks; Panel C shows the evolution for mid-size banks; and Panel D: shows the evolution for specialized banks. The blue line shows the mean value and the red line shows the median value of the Lerner distribution. 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 B5: Evolution of the Boone indicator, quarterly data, for the period 2008:Q1 to 2019:Q1



Source: Banco de México, authors’ calculations.

Notes: This figure shows the evolution of the estimated Boone parameter for the time period 2008:Q1 to 2019:Q1. The shaded areas are the 95% confidence interval around our estimates. An increase in the Boone Indicator is associated to less intense competition. The labels on the horizontal axis indicate the beginning of year.