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Bank Credit Allocation and Sectorial Concentration in Mexico: Some Empirical Evidence*

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Abstract: We empirically assess the extent to which relative growth rates in labor productivity, output, and wage, and growth in a proxy of firms' concentration can explain relative bank credit growth at a sectorial level in the Mexican economy. To that end, we divide our sectors into two groups based on their average concentration. Then, we estimate a panel regression with fixed effects for each group, positing relative credit growth as dependent variable. We document that changes in concentration growth contribute to explaining relative credit growth, particularly so in the group with high average concentration. However, in the group with low average concentration, relative credit growth seems to be also explained by relative labor productivity, output, and wage growth rates. We also discuss some mechanisms that might explain these results. Such mechanisms could lead to counterproductive dynamics between concentration growth and relative credit growth, for which we provide some empirical evidence.

Keywords: Credit, Concentration, Productivity, Mexico.
JEL Classification: E51, J24, L13.

Resumen: Evaluamos empíricamente hasta qué punto los crecimientos relativos de la productividad laboral, el producto, los salarios y el crecimiento de un aproximado de la concentración de las empresas pueden explicar el crecimiento relativo del crédito bancario a nivel sectorial en la economía mexicana. Para tal fin, dividimos nuestros sectores en dos grupos con base en su nivel de concentración promedio. Posteriormente, estimamos una regresión de panel con efectos fijos para cada grupo, postulando al crecimiento relativo del crédito como variable dependiente. Documentamos que los cambios del crecimiento de la concentración explican el crecimiento relativo del crédito, en particular en el grupo con concentración promedio alta. Sin embargo, para el grupo con concentración promedio baja, el crecimiento relativo del crédito parece ser explicado también por los crecimientos relativos de la productividad laboral, del producto y de los salarios. Discutimos también algunos mecanismos que pudieran explicar estos resultados. Dichos mecanismos pueden llevar a dinámicas contraproducentes entre el crecimiento de la concentración y el crecimiento relativo del crédito, para lo cual proveemos evidencia empírica.

Palabras Clave: Crédito, Concentración, Productividad, México.

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1. Introduction

The role of the financial system in an economy has been studied at least since Bagehot (1873). An important strand of the literature has endeavored itself to link financial development with economic growth (e.g., see Rajan and Zingales, 1998, and Levine, 1997). In principle, this process is direct: a well-developed financial system is conducive to a more efficient capital allocation where it will find the best returns and, accordingly, lead to economic growth. In practice, nonetheless, it entails market frictions.

Three broad topics seem to be particularly relevant to gain a better understanding of such a process. First, the extent to which there is a causal relationship in the referred link and, if that is the case, the mechanisms behind it (e.g., see Levine, 2005, and King and Levine, 1993); second, the financing decisions made by firms, which entail a number of economic phenomena, prominently, adverse selection, costly state verification, and moral hazard (e.g., see Freixas and Rochet, 2008); and, third, the role played by the level of competition in the banking sector (e.g., see Claessens, 2009). Still, we believe that relative less attention has been paid to understanding the role of competition across firms and sectors to which financial resources, including bank credit, are allocated.

All things considered, banks evidently care about the characteristics of the firms and sectors to which their funds could potentially be allocated. Under perfect competition, creditors should allocate more resources to more productive and economically active sectors. Nonetheless, in a more general context, the level of market concentration prevalent in a sector could explain part of the banks' decisions.

From the point of view of a banker, more concentration might be desirable. In effect, it may enable the banker to allocate its financial resources to those firms with more market power, partially benefitting from their extraordinary profits. From the point of view of society, for instance, this might be deemed undesirable, since output levels could remain lower, compared to a situation where there is more competition.

In this context, we are interested in empirically assessing the extent to which relative growth in bank private credit can be explained in terms of: i) relative growth in labor productivity; ii) relative growth in economic activity; iii) relative growth in wages; and, iv) growth in a proxy of concentration, in the Mexican economy at a sectorial level. By relative we specifically mean the difference between the growth rates in the sectorial variable of interest and in that same variable in the whole economy. To that end, we divide our sectors into two groups: one with low average concentration and one with high average concentration, as we explain in more detail later. Naturally, we control for some variables that could play a role in explaining the dependent variable.

We document that changes in concentration growth contribute to explaining relative credit growth, in particular, in the group with high average concentration. In contrast, in the group with low average concentration, credit growth seems to be also explained by relative labor productivity, output, and wage growth rates. We ponder a number of possible mechanisms behind these results. First, a type of adverse selection in that a group of sectors could be obtaining credit at the margin based more on their market concentration and less so on factors such as their labor productivity.[1] Second, allocating, contracting, and monitoring credit could be less costly in a concentrated sector. Third, banks might to an extent be able to benefit from firms' extraordinary profits.[2] In tandem, these mechanisms might lead to the presence of counterproductive dynamics between concentration growth and relative credit growth. Additionally, we present some evidence on the potential presence of feedback dynamics between relative credit and concentration growth rates.

2. An Abridged Literature Review

One of our interests is to contribute to a body of literature that examines specific aspects of the Mexican economy surrounding its productivity and growth. We believe that our empirical assessment of credit growth's determinants closely relates to Arias, Azuara, Bernal, Heckman, and Villarreal's (2010) burden of monopoly, Chiquiar and Ramos-Francia's (2009) discussion on the incentives that promote the allocation of resources towards unproductive and rent-seeking activities, and Hanson's (2010) distortions in credit markets, papers that we explain next in some detail. Naturally, there is important work that examines related topics.[3] It goes without saying that we examine a very specific aspect pertaining these issues.

Arias, Azuara, Bernal, Heckman, and Villarreal (2010) discuss a number of problems faced by the Mexican economy. They argue that the following two issues should receive wider attention in policy discussions. First, the fact that the Mexican family is under

[1] In effect, firms with market power tend, for example, to have strong balance sheets and stable profits, features that banks assess when allocating their credit.

[2] Evidently, banks cannot benefit directly from firms' extraordinary profits. They face some competition and firms can opt for other sources of credit. Thus, there are limits to such benefits.

[3] We briefly mention some of that work and its main findings. Barros (2009) studies the *Seguro Popular* program. He finds that its beneficiaries have reduced out-of-pocket health expenditures and shifted from private to public health providers. Yet, he finds that the program has had a negligible effect on their health outcomes. Chiquiar and Hanson (2005) find that Mexican migrants to the U.S. are, on average, more educated than the residents in Mexico. This suggests that there is a positive selection of migrants from Mexico. Haber (2009) studies why the banking system in Mexico provides low levels of credit. He finds evidence in line with the presence of oligopolistic competition and weak property rights. Juarez (2008), assessing a free health care program implemented in Mexico City, documents that workers who receive higher fringe benefits are paid a lower wage. She then argues that informal salaried workers are not necessarily worse off than those in the formal sector. Knox (2008) evaluates the effects of *Seguro Popular* on household health-related consumption and outcomes. She finds increments in health care utilization, but small changes in health outcomes. Levy (2008) argues that despite reform efforts, Mexico has experienced little economic growth. He argues that incoherent social programs have contributed to this and discusses possible reforms to improve such a situation. Urrutia et al. (2015) study the effect of credit conditions on the allocation of inputs and the implications for aggregate total factor productivity (TFP). By building a dataset for Mexican manufacturing, they document that variations in allocative efficiency account for three fourths of aggregate TFP variability.

stress. For instance, they point out that the fraction of children living in families with a single parent has notably increased. This one, among other factors, hinders investment in human capital. Second, the informal sector is considerably large. They argue that this is mostly due to the incidence of monopolies and regulatory burdens.

Chiquiar and Ramos-Francia (2009) assess the role that structural factors may have as determinants of Mexico's economic growth. In particular, they argue that beyond its demand-side challenges, Mexico's low growth also appears to be associated with supply-side characteristics of its economy. One of their key arguments is that Mexico's level of competitiveness seems to reflect an institutional framework that tends to support non-competitive markets and the presence of incentives that encourage the allocation of resources to unproductive rent-seeking activities.

Relatedly, Antón, Hernández, and Levy (2012) assess Mexico's dual social insurance. Specifically, they argue that firms and salaried workers are obliged to contribute for a bundled set of social security programs. On the other hand, non-salaried workers benefit from an unbundled set of similar programs for which they do not contribute. The latter programs are, nonetheless, paid for by the government. They contend that such an arrangement: i) provides workers with inconsistent coverage; ii) encourages fiscal evasion; iii) halts the link between contributions and benefits; and, iv) creates a distortion in the labor market, lowering total factor productivity. The authors put a reform forward that would shift the social insurance taxation from labor to consumption. They argue that their proposal would address the referred issues.

Hanson (2010) reviews the related literature examining a number of arguments on why Mexico has not had higher rates of economic growth. He argues that some of the most relevant internal factors comprise distortions in credit markets, in the supply of nontraded goods, and in the incentives for informality. These factors, in turn, affect productivity adversely. As one key external factor he highlights that Mexico produces a number of goods that China also makes and little of what China consumes.

More generally, Aghion and Griffith (2008) study the effect that competition policy and deregulated entry has on economic growth. They underscore that a positive effect between competition and productivity growth has been empirically documented.

3. Data

We use outstanding bank private credit aggregated monthly data from the *Comisión Nacional Bancaria y de Valores* (*CNBV*). These data are aggregated as a function of six economic sectors.[4] In particular, this credit information entails a substantial number of firms, amounting for a total average of 263,311.16 (Table 1).

[4] The sectorial time series have been constructed by the Financial Stability Division of the Banco de México based on data from *CNBV* using its firm-level classification as a reasonable match to the sectors used by *INEGI*.

We measure market concentration using a Herfindahl-Hirschman Index of bank credit, based on the data from *CNBV*. We believe that this is a sensible measure of general market concentration for reasons we discuss below. To measure economic growth within sectors, we use the Global Indicator of Economic Activity (*IGAE*) sub-indices. To measure productivity, we separately use two types of labor productivity indices from *Instituto Nacional de Estadística, Geografía e Informática* (*INEGI*). To measure the level of wages, we use data from *Instituto Mexicano del Seguro Social* (*IMSS*). In general, we consider their month to month growth rates.

Sector	Mean	Median	Standard Deviation	Coeff. of Variation
Agricultural	11,460.31	12,334.50	2,464.62	0.22
C&T	9,792.69	9,810.50	1,459.45	0.15
Commercial	98,679.74	100,581.00	14,504.11	0.15
Construction	13,247.24	13,807.50	2,267.88	0.17
Industrial	31,503.44	31,136.50	4,528.81	0.14
Services	98,627.72	102,540.00	14,104.40	0.14
Total	263,311.16	271,906.00	38,570.65	0.15

Table 1. Statistics for the Number of Firms by Sector
Notes: These are time series statistics from the July 2009-December 2016 period. C&T stands for communications and transport.
Source: With data from *CNBV*.

We ponder six sectors: agricultural (including livestock), commercial, construction, communications and transportation (C&T), industrial (i.e., industrial manufacturing), and services (excluding financial services). The following sectors are not considered in our study: mining, generation, transmission and distribution of electricity, water and gas supply, government services, and financial services. Our data covers the period from July 2009 to December 2016.

As mentioned, the Herfindahl-Hirschman Index (HHI) is constructed based on sectorial credit concentration. We believe that this is a sensible measure of market concentration for several reasons. Among them, we highlight the following ones. Bigger firms, e.g., in terms of sales, assets or employees, are typically offered more credit.[5] On the other hand, small- and medium-sized firms face more notable asymmetric information issues, tend to lack significant collateral and, thus, are typically unable to obtain substantial amounts of credit.[6]

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[5] For instance, the World Bank Group (2014) has documented that throughout Latin America and the Caribbean small and medium enterprises (SMEs) are more credit constrained than large ones. The definition of size that they used is in terms of the number of employees, below 100 for SMEs and above 100 for large ones.

[6] Nguyen and Qian (2012) find that in developing countries small firms are less likely to pledge collateral for formal loans compared to large firms. Hanson (2010), citing Haber (2005),

On a related matter, we use the sectorial cost of credit as a control. We have credit cost measured in terms of total and marginal credit rates. In other words, the cost of outstanding credit and that of an additional credit. Similarly, we ponder the difference between the cost of credit for a sector and the cost of credit for all sectors. For the latter, we use a weighted average credit interest rate, in which weighs are based on the sectorial contributions toward GDP.[7]

To set the stage, we explore our data in more detail. First, reconsider the statistics on the number of firms in each sector for the July 2009-December 2016 period (Table 1). Based on the average number of firms, the commercial and services sectors have the largest levels, while C&T has the lowest one.[8] As an indicator of their variability, we present their coefficients of variation, which put the agricultural sector at the top. After it, all sectors share similar levels. Needless to say, the average number of firms and their variability in each sector depend on many characteristics, among which concentration is one of them.

In terms of the average outstanding real credit, the industrial sector has maintained the highest level, followed by the services one (Table 2). The commercial and construction sectors trail closely, while the C&T and agricultural sectors rank last, in that same order. We note that, relative to its mean, the level of outstanding credit varies more in the C&T sector and less so in the construction sector.

Sector	Mean	Median	Standard Deviation	Coeff. of Variation
Agricultural	53,020.63	51,621.22	10,744.67	0.20
C&T	58,924.30	52,077.13	17,466.89	0.30
Commercial	265,373.30	268,500.00	59,191.76	0.22
Construction	270,369.70	271,688.40	17,067.28	0.06
Industrial	365,590.10	349,135.40	42,574.62	0.12
Services	296,140.70	279,518.20	70,150.21	0.24

Table 2. Outstanding Credit by Sector Statistics
Units: (December 2016) Million Pesos, except for the coefficient of variation.
Sample Period: July 2009 - December 2016.
Source: With data from *CNBV*.

Next, consider the size of each sector relative to GDP (Figure 1). The services sector comes first, followed by the industrial and commercial ones, which show a similar level

explains that while the bankruptcy provisions were changed in Mexico after the 1994-1995 banking crisis, they did little to augment loans that are difficult to collateralize.

[7] In the few cases in which we use weighted averages based on GDP contributions, we assume constant monthly weights during the same quarter. This is reasonable given that the referred contributions change little between quarters. See Table A1 in the appendix for details.

[8] The average refers to the mean of the time series, i.e., its average through time.

by the end of 2016. Construction and C&T sectors are next, with the latter being three percentage points ahead. The last one, in terms of size relative to GDP, is the agricultural sector. Naturally, concentration is one among other variables that can play a role in the determination of a sector's size.

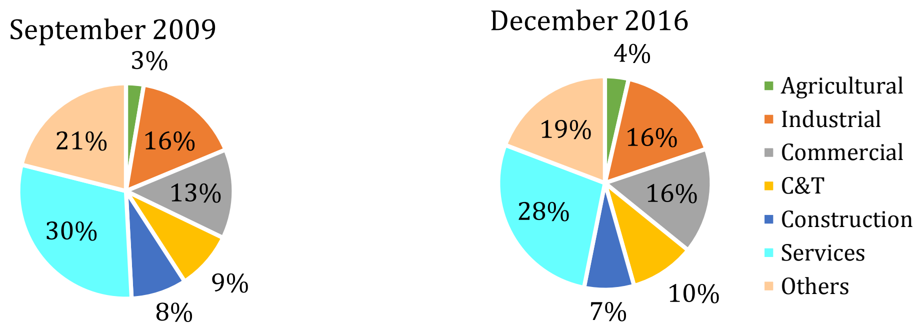

Figure 1. Sector's Size as a Proportion of GDP
Note: Others include: mining, generation, transmission and distribution of electricity, water and gas supply, and government services sectors.
Source: *INEGI*.

We next examine the dynamics of the Herfindahl-Hirschman Index (HHI).[9] To begin with, if sector A has a higher HHI value compared to sector B, then sector A has a higher level of concentration, reflecting a lower level of competition. There are at least three notable patterns in these time series (Figure 2). First, the sector with more concentration is, patently, communications and transportation (C&T). Moreover, its tendency has not changed in recent years.

Second, on the other hand, a trend toward less concentration is shown by the rest of the sectors. Among them, construction seems to have maintained a higher concentration level, and the commercial sector has been, in general, the less concentrated one. The concentration of the industrial sector decreases and then, after an apparent inflection point, rises once again.

Third, evidently, there is a marked change in the C&T's HHI around in 2013, and then once again in 2015.

[9] The magnitudes of regular HHIs are in some cases interpreted in terms of the absolute level of competitiveness in a given market (e.g., see U.S. Department of Justice and the Federal Trade Commission, 2010). For example, a HHI below 100 is interpreted as a magnitude indicating a highly competitive industry. As mentioned, the HHIs we use are constructed based on sectorial credit concentration. Thus, their magnitudes cannot necessarily be interpreted in the same way.

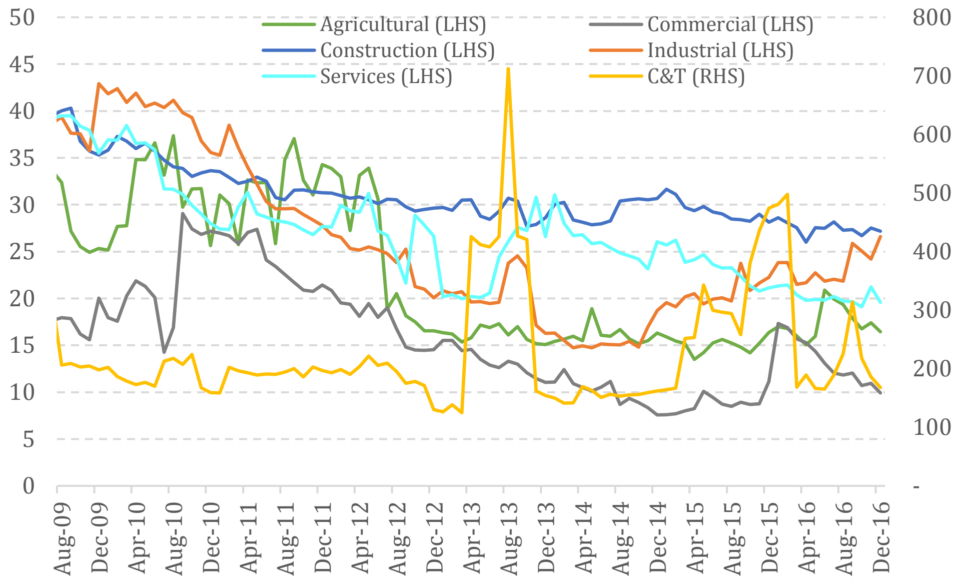

Figure 2. Herfindahl-Hirschman Index (HHI) by Sectors
Frequency: Monthly.
Units: HHI × 10,000.
Source: Based on credit data from *CNBV*.

We next consider one complementary index, the participation of credit of the top-ten firms having the most credit, with respect to the total (Figure 3).[10] As an example, consider that in the services sector in December 2016 the top-ten firms have 10.7% of the outstanding credit. Moreover, based on Table 1, we know that there is an average of 296,140 firms in the referred sector. Thus, the message that this index conveys is not different from the one HHIs tell. A notable level of concentration is present in all sectors.

Moreover, the means of relative credit growth rates markedly differ across sectors (Table 3). They go from a negative value in the construction sector to a positive one in the C&T sector. Their standard deviations are fairly heterogeneous. They start at a low level in the construction sector and reach a high level in the C&T sector. On the other hand, their correlations display different magnitudes and signs. These statistics can be associated with sectorial economic shocks as well as credit decisions taken by banks, among other factors.

[10] This index is akin to a concentration ratio. As is known, this type of indices are less informative that the HHI.

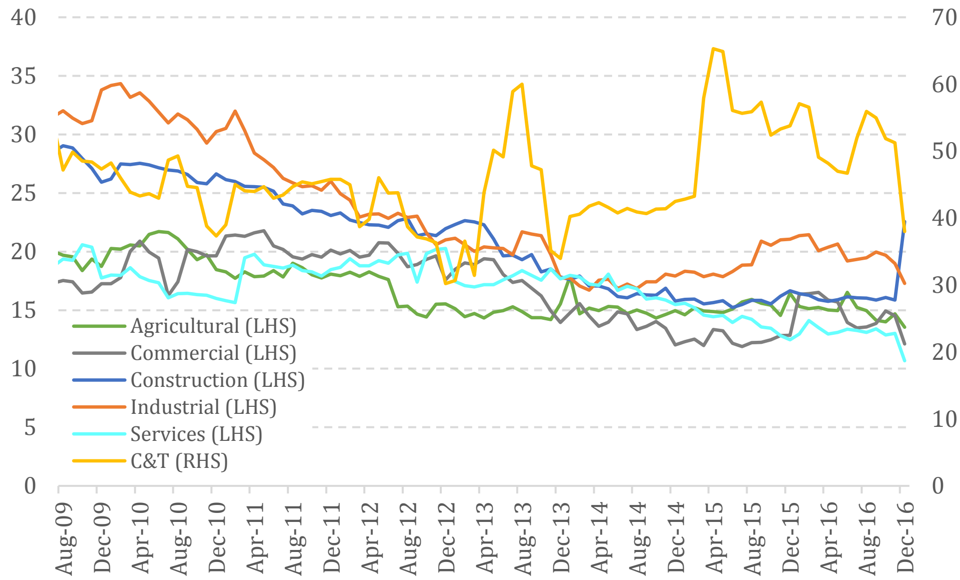

Figure 3. Percentage of Credit Allocated to the 10 Firms with Most Credit by Sector
Frequency: Monthly.
Source: With data from *CNBV*.

	Agricultural	Commercial	Construction	C&T	Industrial	Services
Mean	0.24	0.34	-0.49	0.54	-0.10	0.24
Std. Dev.	1.70	0.93	0.85	4.74	0.81	1.07
Agricultural	1					
Commercial	-0.0132	1				
Construction	-0.1922*	0.0940	1			
C&T	-0.3887*	-0.3121*	-0.1720	1		
Industrial	0.0215	-0.4855*	-0.3097*	-0.0060	1	
Services	0.1665	-0.1159	-0.1720	-0.3563*	-0.4585*	1

Table 3. Sectorial Relative Monthly Credit Growth Statistics
Notes: We estimate the relative growth rate as the difference between the growth of credit of the sector and the growth of aggregate credit. An asterisk indicates that a correlation is statistically different from zero at a 10% confidence level.
Source: With data from *CNBV*.

Firms typically have several sources of credit. However, they mainly rely on their suppliers and banks. First, we make the following assumptions on the former source: i) it commonly relates to their shorter term financial requirements; and, ii) accordingly, their average maturity is less than that of bank credits. In essence, it is an imperfect substitute for bank credit.[11]

[11] Banco de México's (2017) survey "*Evolución del Financiamiento a las Empresas durante el trimestre octubre-diciembre de 2016*" documents that the average maturity of loans to clients is 60 days. We note that the cited survey is representative for the services, manufacturing, and commercial sectors. Still, we find it indicative of the average maturity of this type of credit.

The second main source is bank credit.[12] Based on the *CNBV* data, we have that for the low concentration group, the average maturity for a marginal credit is slightly above one year. On the other hand, for the high concentration group, the average maturity for a marginal credit is approximately two and a half years. Additionally, a key source of financing is a firm's own resources (e.g., see World Bank Group, 2014).[13]

We think that the seasonal components of our times series are important in our analysis for several reasons. First, intuitively, a bank would not deny a hotel credit just before summer vacations on the grounds that its expected profits, adjusted for seasonality, are low. Second, based on the *CNBV* data, the average maturity of a marginal credit is around a year and a half. Thus, we ponder that, in general, the average maturity is not sufficiently long for seasonal effects to become negligible. Three, even in advanced financial markets, seasonality has been found to be relevant in credit market dynamics, both in terms of prices and volumes (e.g., see Murfin and Petersen, 2016).[14] In fact, if we adjust some variables for seasonality some of our results do not hold, which suggests the relevance of its role in our study.[15]

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[12] Firms in Mexico typically have six sources of credit. The third one is from firms in the same corporate group or from its headquarters. The other three are: development banks, banks domiciled abroad, and debt issuance. However, the percentage of firms in each of the last three sources in 4Q-2016 was 5.6%, 5.9%, and 0.4%, respectively, of the total. (Source: Banco de México (2017) "*Evolución del Financiamiento a las Empresas durante el trimestre octubre-diciembre de 2016*."). We note that such a survey is representative at a national level for the services, manufacturing, and commercial sectors. In addition, the World Bank's (2014) "Enterprise Survey" documents that, besides their own resources, the two main sources of financing for working capital are banks and supplier credit. The referred survey "is a firm-level survey of a representative sample of an economy's private sector." They interviewed 12,855 enterprises in 30 Latin American and Caribbean countries following the standard ES global methodology. See also Kuntchev, Ramalho, Rodríguez-Meza, and Yang (2014).

[13] We underscore that the average maturities are in line with their concentration level. In effect, the group with a higher average concentration obtains marginal credits with a longer average maturity. Although using credit maturity as a measure of concentration is plausible, one would need to control for variables such as the typical horizons of the projects in each sector.

[14] For instance, Murfin and Petersen (2016) study the corporate credit market's seasonality. In particular, they argue that the market for corporate credit is characterized by seasonal variation in terms of prices and volume of new lending. What is more, they state that "The presence of pronounced seasonal variation in the cost of financial capital […] is unexpected in a modern and diverse economy with well-developed capital markets. In theory, storing capital should be very low cost and, while individual industries may have specific seasonal funding demands, one might expect the aggregate seasonal component across a diverse set of industries to be low." On a related subject, Heston and Sadka (2008) have documented seasonal effects in the cross-section of stock expected returns. They find that such effects are independent of size, industry, earning announcements, dividends, and fiscal years.

[15] For example, when we adjust *IGAE* growth rates for seasonal effects, it is not statistically significant in our panel regression estimations.

We note that the credit and HHI times series correspond to firms that have obtained bank credit. On the other hand, output, productivity, and wages time series entail, in principle, all firms in the economy; i.e., those that have received bank credit and those that have not. However, it is their generality that allows us to use them as explanatory variables.

In order to match our credit and HHI time series with the *IGAE* sub-indices, we use some approximations. First, the indicator for the agricultural sector is approximated by the *IGAE* for primary activities. The latter, in addition, includes fishing and forestry activities.[16] Second, to estimate the *IGAE* for (non-financial) services, we use its subsectors' series, constructing their weights based on their contributions toward the GDP. The rest of the subindices have, in general, a direct match (see Tables 4A, 4B, and A3 in the appendix for details).

On the Labor Productivity Indices (LPIs), we have three general comments. First, since such series are in quarterly frequency, we have used cubic interpolation to temporally disaggregate them to a monthly frequency. In this process, we make each quarterly data point coincide with the observed datum.

Second, such indices are available in two different, although related, measures. The first one is calculated as a production value index over an employed personnel index. It is available for the overall economy and for each of the sectors we have considered. In addition, we note that the commercial sector uses sales instead of production. The second measure uses a production value index over an hours-worked index, and is available for the economy as a whole, but only for the agricultural, construction, and industrial sectors.

Third, we use the primary activities labor index as a proxy for the agricultural sector. Moreover, since the C&T subsectors have separate indices, we have taken a weighted average of such indices based on their contributions toward GDP. Likewise, the commercial index is available separately for retailers and wholesalers. Since there seems to be insufficient information for the referred subsectors, we take their average. As the main labor productivity index, we use the first one since it has the broadest sectorial coverage. Still, we use the second one as a robustness check. The associated results of the latter are described in the appendix.

We use wages associated with workers affiliated to *IMSS*, measured in pesos per day. These are available for a number of sectors and the match with the sectors for HHI and credit is direct in three cases, the other three cases being the agricultural, services, and industrial sectors. The first has the same caveats as those for the *IGAE* and the productivity index. The second uses the wage of services for companies and individuals sector as an approximation. The third uses the wage of the transformation industry as a proxy. These series could affect the low concentration group more.

[16] In our estimated sample, the agricultural sector (including livestock) accounts for more than 90% of the primary sector.

In what follows, we describe some of the variables that we have considered as controls. Mexico, being a small open economy, is exposed to shocks to its foreign exchange rate. Some sectors, in particular, the commercial and industrial ones, can be directly affected by such shocks. Hence, we separately explore the extent to which (changes in) nominal and real FX rates might have an impact on the relative growth of credit. The nominal exchange rates are from *Banco de México* and the real FX rates are from the Bank of International Settlements (BIS). We present the associated results in the appendix.

We also use imports and exports' real growth rates as controls. Due to their importance and data availability, we use exports' time series for the agricultural, manufacturing, and services sectors. For the rest, we use a general exports series. Similarly, total imports are used as controls for each sector. These series have a monthly frequency, except for services' exports, which has a quarterly frequency. Thus, we temporally disaggregate them using cubic interpolation. Their source is *INEGI*.

We have a number of comments on possible measurement errors in our variables. First, the period when a credit is approved and when it is actually allocated (and thus recorded) is not necessarily the same. Likewise, credits are subject to possible extensions in size and term. This might lead to some measurement errors. By the same token, the HHI index that we use might be subject to such errors. This might also apply to a number of variables in our dataset for other reasons. For instance, as said, the labor productivity indices are disaggregated from a quarterly frequency to a monthly one. As another case, we estimate weighted averages based on the variable's contribution toward GDP, which evidently are approximations.

Second, as is known (e.g., see Pischke, 2007), measurement errors in variables might lead to attenuation bias. This means that, in a linear model, the coefficients associated with variables having these errors tend to have a bias toward zero.[17] To tackle this potential issue, we take 3-month weighted averages for: relative credit, relative labor productivity, relative output, relative wage, HHI, exports, and imports growth rates. The associated weights add to one and decrease with the lag.[18] Thus, our working

[17] As an example consider the following linear regression model $y = x\beta + e$. Suppose that we can only measure x with an error. Thus, $\hat{x} = x + u$ where u is a measurement error, and $E_t(u) = 0$. We assume that u is iid and uncorrelated with y and x. Thus, the OLS estimate of β is given by $\hat{\beta} = cov(\hat{x}, y)/var(\hat{x}) = \beta + cov(x, y)/var(u)$, which is smaller than β if it is positive and greater than β if it is negative. Thus, it is biased toward zero.

[18] Since we have assumed an iid measurement error in the relative growth rates, an equally weighted quarterly average would be preferable. On the other hand, a weighted quarterly average with higher weights for the most recent observations would be better in terms of the mitigation of the possible presence of endogeneity, given the use of economic growth as a regressor. Thus, we use 0.45, 0.30, and 0.25 as weights; e.g., we have that for a given relative growth rate g, its weighted average is $\hat{g}(t) = 0.45g(t) + 0.30g(t-1) + 0.25g(t-2)$. Our main results are generally robust to variations in these weights provided that they add to one (e.g., 0.45+0.30+0.25=1.00) and each weight decreases as its associated lag increases (e.g., 0.45>0.30>0.25).

assumption is that the variables' relative growth rates have additive iid measurement errors.

We generally use relative month to month growth rates, except for three cases, for which we consider their month to month growth rates directly. The first case is HHI growth. As mentioned, HHI is already a relative measure in terms of a specific sector. The second case is when a given variable is only available for the whole economy (e.g., imports). The third one is when the variable is common to all sectors (e.g., the exchange rate). In fact, in the second and third cases, it is not direct to estimate a relative growth rate. See Tables 4A, 4B, and A3 in the appendix for further details.

In this context, month to month growth rates have one advantage. Short-term growth rates allow the econometrician to consider simpler models. In general, with long-term growth rates, more variables could have a role, which would otherwise have to be part of the regressors. We explore this issue in the appendix.

Variable/Sector	Agricultural	Commercial	Communication and Transportation (C&T)	Construction	Industrial (Manufacturing industries)	(Non-financial) Services	Total	Variable Used
Credit	Agricultural	Commerce	Communication and Transportation	Construction	Industry	Services	-----	3-Month Weighted Average MoM Relative Credit Growth
Credit Interest Rates Total	Agricultural	Commerce	Communication and Transportation	Construction	Industry	Services	-----	3-Month Weighted Average MoM Relative Credit Interest Rates Total
Credit Interest Rates Marginal	Agricultural	Commerce	Communication and Transportation	Construction	Industry	Services	-----	3-Month Weighted Average MoM Relative Credit Interest Marginal Rates Total
HHI	Agricultural	Commerce	Communication and Transportation	Construction	Industry	Services	-----	3-Month Weighted Average MoM HHI Growth
Labor Productivity Index (LPI), based on employed personal[1/]	Primary Sector	Sector 43: Wholesalers. Sector 46: Retailers.	Sector 48-49: Transportation, mailing and storage. Sector 51: Mass media information	Construction Firms	Sectors 31-33: Manufacturing industries	Labor productivity index for non-financial services.	Total	3-Month Weighted Average MoM Relative Growth
Labor Productivity Index (LPI), based on hours-worked[1/]	Primary Sector	Total	Total	Construction Firms	Sectors 31-33: Manufacturing industries	Total	Total	3-Month Weighted Average MoM Relative Growth

Table 4A. Times Series Description.

1/Source: *INEGI*. 2/Source: *INEGI*. Retrieval date: April 5th, 2017. 3/*Salario Diario Asociado a Trabajadores Asegurados en el IMSS por Sector de Actividad Económica.* Source: *IMSS*. Retrieval date: April 18th, 2017. 4/In Mexican pesos (we use monthly average MXN/USD exchange rate), deflated using the CPI. 5/Source: Banco de México.6/Source: BIS, broad index. Retrieval date: June 5th, 2017.

Variable/Sector	Agricultural	Commercial	Communication and Transportation (C&T)	Construction	Industrial (Manufacturing industries)	(Non-financial) Services	Total	Variable Used
Economic Growth (IGAE)2/	Primary Sector	43-46 Commerce	48-49-51 Transportation, mailing and storage; mass media information.	23 Construction	Sectors 31-33: Manufacturing industries	54-55-56 Professional, scientific and technical services; Corporate; Business support services and waste management and remediation services 61-62 Educational services; Health and social work services 71-81 Cultural and sporting recreation services, and other recreational services; Other services except government activities 72 Temporary accommodation and food and beverage preparation services	Global Economic Activity Indicator (Indicador Global de la Actividad Económica)	3-Month Weighted Average MoM Relative Growth
Wages3/	Agriculture, livestock, forestry, hunting and fishing	Commerce	Transportation and communications	Construction	Processing industries	Services for companies and individuals	Total	3-Month Weighted Average MoM Relative Growth
Imports4/	Total (non-oil)	Total (non-oil)	Total (non-oil)	Total (non-oil)	Total (non-oil)	Total (non-oil)	Total (non-oil)	3-Month Weighted Average MoM Real Growth
Exports4/	Agricultural	Total (non-oil)	Total (non-oil)	Total (non-oil)	Manufacturing Industry	Services Exports	Total (non-oil)	3-Month Weighted Average MoM Real Growth
Exchange Rates (nominal5/ **and real**6/**)**	-------	-------	-------	-------	-------	-------	Total	3-Month Weighted Average MoM Growth

Table 4B. Times Series Description.

1/Source: INEGI. 2/Source: INEGI. Retrieval date: April 5th, 2017. 3/*Salario Diario Asociado a Trabajadores Asegurados en el IMSS por Sector de Actividad Económica*. Source: *IMSS*. Retrieval date: April 18th, 2017. 4/In Mexican pesos (we use monthly average MXN/USD exchange rate), deflated using the CPI. 5/Source: Banco de México. 6/Source: BIS, broad index. Retrieval date: June 5th, 2017.

4. Model

It is important to state from the outset that we do not intend to estimate nor calibrate a model. Nonetheless, we tweak a standard profit maximizer firm model that provides a useful framework to our discussion. In this respect, we assume that credit is a non-decreasing function of the firm's profits. Evidently, financing decisions across firms are not trivial processes, for instance, they depend on the stage of the firm's life cycle. Yet, we presume that at a sectorial level such an assumption is reasonable.

Accordingly, we focus on a firm profit maximization model, which can potentially demand credit. A firm i maximizes its profits $\Pi_{t,i}$ at time t, choosing the input vector $\boldsymbol{z}_{t,i}$, with an exogenous price vector $\boldsymbol{w}_{t,i}$:

$$\Pi_{t,i} = \max_{\boldsymbol{z}_{t,i} \geq 0} P_{t,i}\big(q_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_i}\big)\, q_{t,i}, - f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i}), \qquad (1)$$

where $P_{t,i}$, which is endogenous, is the price of the good or service and a function of output $q_{t,i}$, the economic growth of the sector the firm belongs to $\gamma_{t,i}$, market concentration $\mu_{t,i}$ and possibly other variables $\boldsymbol{\theta_i}$**.** In addition, we assume that $f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i})$ is a $C^1(\mathbb{R}^{2M})$ function, where M is the number of inputs, each one having an associated price.

Since we are interested in the variations in credit growth due to variations in labor productivity, we use the following change of variable $\ell_{t,i} = q_{t,i}/L_{t,i}$:

$$\max_{\boldsymbol{z}_{t,i} \geq 0} P_{t,i}\big(L_{t,i}\ell_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_i}\big)\, L_{t,i}\ell_{t,i}, - f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i}),$$

where $\ell_{t,i}$ is labor productivity and $L_{t,i}$ labor input. Evidently, the latter is a component of $\boldsymbol{z}_{t,i}$.

We assume that the cost function $f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i})$ is non-decreasing with respect to each input; i.e., as the firm uses more of an input, it incurs in equal or greater costs. Similarly, $f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i})$ is also a non-decreasing function with respect to each price $w_{t,i,j}$, with $j = 1, \dots, M$.

Suppose that there exists an optimal point $\boldsymbol{z}^*_{t,i} \in \mathbb{R}^M$. Thus, it has to satisfy equation (1). Using the envelope theorem, we have that a change in the optimal profit of the firm with respect to some parameter $Y_{t,i}$ can be expressed as the partial derivative of the function $P\big(L_{t,i}\ell_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_i}\big)L_{t,i}\ell_{t,i} - f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i})$ with respect to the parameter of interest:

$$\frac{d\Pi_{t,i}}{dY_{t,i}} = \frac{\partial}{\partial Y_{t,i}} \left[P_{t,i}\big(L_{t,i}\ell_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_i}\big)\, L_{t,i}\ell_{t,i} - f(\boldsymbol{w}_{t,i}, \boldsymbol{z}^*_{t,i})\right], \qquad (2)$$

evaluated at $\boldsymbol{z}^*_{t,i}$.

Accordingly, changes in the firm's profits with respect to market concentration, economic growth, labor productivity, and input prices can be characterized by the following partial derivatives:

i) $\frac{d\Pi_{t,i}}{d\mu_{t,i}}\left(\boldsymbol{z}_{i,t}^{*}, \ell_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_t}\right) = \frac{\partial P_{t,i}}{\partial \mu_{t,i}} L_{t,i}\ell_{t,i}$;

ii) $\frac{d\Pi_{t,i}}{d\gamma_{t,i}}\left(\boldsymbol{z}_{i,t}^{*}, \ell_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_t}\right) = \frac{\partial P_{t,i}}{\partial \gamma_{t,i}} L_{t,i}\ell_{t,i}$;

iii) $\frac{d\Pi_{t,i}}{d\ell_{t,i}}\left(\boldsymbol{z}_{i,t}^{*}, \ell_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_t}\right) = \left(\frac{\partial P_{t,i}}{\partial \ell_{t,i}} L_{t,i}\right) L_{t,i}\ell_{t,i} + P_{i,t}L_{t,i}$; and,

iv) $\frac{d\Pi_{t,i}}{dw_{t,i,k}}\left(\boldsymbol{z}_{i,t}^{*}, q_{t,i}, \gamma_{t,i}, \mu_{t,i}; \boldsymbol{\theta_t}\right) = -\frac{\partial f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{i,t}^{*})}{\partial w_{t,i,k}}$ for $k = 1, \dots, M$,

each evaluated at $\boldsymbol{z}_{t,i}^{*}$.

Our next step is to characterize the sign of each of these partial derivatives.

i) Concentration

An increase in market concentration $\mu_{t,i}$ will usually increase profits. Note that given $\ell_{t,i}$, $L_{t,i}$ is uniquely determined by $q_{t,i}$. Thus, we can rewrite the first order condition of $L_{t,i}$ in terms of $q_{t,i}$. The optimality condition of $q_{t,i}$ is then:[19]

$$P_{t,i}\left(\frac{1}{\varepsilon_{t,i,D}} + 1\right) = \partial f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{i,t}^{*})/\partial q_{t,i},$$

where $\varepsilon_{t,i,D}$ is the elasticity of demand faced by the firm and $\partial f/\partial q_{t,i}$ is its marginal cost.

Up to this point, we have not defined $\mu_{t,i}$ explicitly. We find it useful to define it equal to the Lerner index, which is a standard measure of concentration. Thus, we let $\mu_{t,i} \equiv (P_{t,i} - \partial f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{i,t}^{*})/\partial q_{t,i})/P_{t,i}$ and rewrite the last equation as:

$$P_{t,i}\left(1 - \mu_{t,i}\right) = \partial f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{i,t}^{*})/\partial q_{t,i}. \qquad (3)$$

We note that $\mu_{t,i}$ belongs to the interval [0, 1] since its marginal cost is positive and it is necessarily less than or equal to the price.[20] In particular, if $\mu_{t,i} = 0$, then the price equals the marginal cost. On the other hand, if $\mu_{t,i} > 0$ then the firm charges a markup

[19] Our production function does not explicitly depend on the quantity of goods produced. Yet, given the vector $\boldsymbol{w}_{t,i}$ the optimal $\boldsymbol{z}_{t,i}$ uniquely determines $q_{t,i}$. Thus, alternatively, one could rewrite the cost function purely in terms of $q_{t,i}$ (for a fixed vector $\boldsymbol{w}_{t,i}$). One can then rewrite the optimality condition of $q_{t,i}$ as $P'_{t,i}(q_{t,i})q_{t,i} + P_{t,i} = C'(q_{t,i})$, i.e., marginal revenue equals marginal cost.

[20] If the marginal cost is greater than the price, then the firm is not optimizing. If it is always the case that the marginal cost is greater than the price, then the optimal solution is setting production equal to zero.

over its marginal cost, as determined by (3). Noting that $\mu_{t,i} = -1/\varepsilon_{t,i,D}$, the referred optimality condition implies that the marginal revenue equals the marginal cost.

Finally, we have two cases. Consider first the case of constant marginal costs as a function of $q_{t,i}$. As $\mu_{t,i}$ increases in (3), its price would need to decrease to maintain the optimality condition. Hence, we have that $\partial P_{t,i}/\partial \mu_{t,i} > 0$. Moreover, using equality i), it follows that $\partial \Pi_{t,i}/\partial \mu_{t,i} > 0$. Consider next more general marginal costs. Based on (3), we obtain that $\partial P_{t,i}/\partial \mu_{t,i} = (\partial f(\boldsymbol{w}_{t,i}, \boldsymbol{z}^*_{i,t})/\partial q_{t,i})/(1-\mu_{t,i})^2$, which is non-negative. Hence, the result also holds with a more general cost function.

ii) Economic Growth

One could generally ponder that greater sectorial economic growth leads to a higher demand for goods and services of the firm, obtaining higher profits, all else being equal. A possible interpretation of greater sectorial growth is an outward shift in the demand for the firm's products or services.

iii) Labor Productivity

In order to analyze the sign of the third equation, we swap back our change of variable to $q_{t,i} = L_{t,i}\ell_{t,i}$. This implies that:

$$\frac{\partial \Pi_{t,i}}{\partial \ell_{t,i}} = L_{t,i}\frac{\partial \Pi_{t,i}}{\partial q_{t,i}}$$

Thus, using (1), and the product rule, we have that:

$\frac{\partial \Pi_{t,i}}{\partial \ell_{t,i}} = \frac{\partial \Pi_{t,i}}{\partial q_{t,i}} L_{t,i} = \left(q_{t,i}\frac{\partial P_{t,i}}{\partial q_{t,i}} + P_{t,i}\right) L_{t,i} = \left(\frac{\partial (P_{t.i}\, q_{t,i})}{\partial q_{t,i}}\right) L_{t,i}$, evaluated at $\boldsymbol{z}^*_{t,i}$.[21]

The last expression indicates that a change in profits with respect to labor productivity is proportional to its marginal revenue. Typically, marginal revenue is greater or equal to zero, else the firm would not be optimizing. A change in profits with respect to labor productivity should be in general non-negative. Consequently, if productivity increases, the cost of labor per unit of output would be lower, all else being equal.

iv) Wages

Based on the fourth relation, if $f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i})$ is a non-decreasing function with respect to each input price, we have that profits would be a non-increasing function with respect to each input price. This is in line with the usual assumptions made on $f(\boldsymbol{w}_{t,i}, \boldsymbol{z}_{t,i})$. In our empirical analysis, we specifically control for wages.

[21] Note that since in this case $L_{t,i}$ is fixed:
$\partial f/\partial q_{t,i} = (\partial f/\partial \ell_{t,i})(\partial \ell_{t,i}/\partial q_{t,i}) = (\partial f/\partial \ell_{t,i})(1/L_{t,i}) = 0$.

Up to this point, we have referred to a firm optimizing its profits. In our empirical exercises, we refer to sectors and, more broadly, to groups of sectors. Thus, we make an aggregation assumption in that the relations that we have collected from this model are maintained for groups of sectors.

The process of assigning, contracting and monitoring a credit involves, at least, three mechanisms: adverse selection, costly state verification, and moral hazard. Evidently, these are present in different types of financial transactions, including those that we have a keen interest about.

In this context, first, we hypothesize on the possible presence of some type of adverse selection in the sense that a number of sectors might be obtaining credit based more on their concentration and less so on factors such as their productivity. Second, if we suppose that a bank has to allocate a unit of credit and that there is a fixed cost in verifying its feasibility, contracting, and monitoring, doing so in a concentrated sector would typically be less costly. For instance, fewer firms would need to be assessed. Third, banks might be able to benefit from firms' extraordinary profits. In tandem, all of these elements might lead to the presence of counterproductive dynamics between concentration growth and relative credit growth.

In sum, we have the following central empirical implications, all else being equal. First, as the prospects of extraordinary profits increase, a banker is more willing to allocate additional credit to such a sector. Second, as economic activity rises in a specific sector, more credit could be assigned to it. Third, as productivity increases, a sector is able to achieve more output with less labor, increasing its profits and, thus, demand for credit. Fourth, as costs of inputs (e.g., wages) increase, less credit should be assigned to such a sector. We also separately control for a set of potentially relevant variables.

5. Panel Data Regressions

As mentioned, our aim is to empirically assess the extent to which relative credit growth is determined by relative growth in economic activity, productivity, wage, and growth in a proxy of market concentration, while accounting for a set of controls.

To that end, we have divided our six sectors into two groups in terms of their sample average HHI. Specifically, the low concentration group is made of the commercial, agricultural and industrial sectors, and the high concentration group is made of the service, construction, and communication and transportation (C&T) sectors. We note that the average HHI of the first group is 21, and the average HHI of the second group is 95. We underscore that the same two groups are maintained when one only considers the second half of the sample to estimate their average concentrations.[22]

On a related matter, using economic growth as a regressor might entail some endogeneity. In effect, not only can economic growth lead to more credit, but more

[22] Further below, we report a number of panel data estimations for which we vary one of these groups.

credit might lead to economic growth, in general and at a sectorial level. To mitigate this, in addition to our conventional panel data regressions, we also estimate parallel regressions with economic growth lagged one month.

All in all, our generic panel regression model is as follows:

$$c_{i,t} = \beta_0 + \beta_1 hhi_{i,t} + \beta_2 g_{i,t} + \beta_3 lpi_{i,t} + \beta_4 w_{i,t} + \boldsymbol{\beta_5 X_{i,t}} + \epsilon_{i,t} \tag{4}$$

where $c_{i,t}$ is the relative growth in outstanding credit, $hhi_{i,t}$ is the HHI growth, $g_{i,t}$ is relative economic growth, $lpi_{i,t}$ is relative labor productivity growth, and $w_{i,t}$ is relative wage growth, all for sector i in month t.

Analytically, by the relative growth of variable $\nu_{i,t}$ we mean $\nu_{i,t} \equiv \nu'_{i,t} - \nu_t$; where $\nu'_{i,t}$ is the month-to-month growth for sector i in period t, and ν_t is the month-to-month growth in period t for the whole economy. As said, by taking such differences, we control for common factors that can affect variables in the same way; e.g., inflation.

We have that $\boldsymbol{X_{i,t}}$ denotes the set of control variables. In most cases, these are individual for each sector; in other cases, they are common to all sectors. In addition, $\epsilon_{i,t}$ is the error term, for which we have assumed a fixed effects model. With it, we control for unobserved sectorial heterogeneity that is constant through time. An example of this type of heterogeneity is the access that sectors have to different collaterals, which affect their capacity to obtain credit. For the most part, the characteristics of their collaterals do not change through time but differ across sectors.

We have several comments on our initial estimations (Table 5). First, the panel data regressions on the first and second columns are, we believe, surprising. Indeed, under a modestly efficient credit market, there is in principle no reason why concentration growth should be strongly correlated with relative credit growth, as is the case for the high concentration group (second column).

By way of example, consider two polar cases, beginning with a highly competitive sector. In this first case, an increase in concentration would give a handful of firms more capacity to demand credit. Yet, this would only entail a small correlation between HHI growth and relative credit growth. On the other hand, consider a highly concentrated sector. In this case, a further increase in concentration would, possibly, lead to a greater demand for credit, increasing the correlation between the referred variables. Hence, it is only in a concentrated sector that one would expect to identify such a correlation.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0438 (3.52)***	0.171 (13.69)***	0.0435 (4.27)***	0.171 (13.69)***	0.0435 (4.35)***	0.171 (13.68)***	0.0558 (4.98)***	0.171 (13.65)***
Relative Economic Growth			0.0815 (11.23)***	0.0807 (0.79)				
Relative LPI Growth					0.205 (11.88)***	-0.0507 (-0.57)		
Relative Wage Growth							-0.479 (-8.08)***	0.141 (0.40)
Constant	0.160 (2.17)**	-0.0240 (-0.18)	0.0694 (1.14)	-0.0266 (-0.20)	0.119 (2.01)**	-0.0166 (-0.12)	0.177 (2.68)***	-0.0144 (-0.11)
N	261	261	261	261	261	261	261	261
R^2	0.046	0.422	0.361	0.423	0.385	0.422	0.240	0.422
adj. R^2	0.035	0.415	0.351	0.414	0.375	0.413	0.228	0.413

Table 5. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

In effect, the coefficients of determination in each case markedly differ. While the low concentration has an adjusted R^2 of 0.04 (first column), the high concentration group has it at 0.42 (second column). We believe that the latter suggests the possible presence of some type of friction. In addition, these statistics are relevant benchmarks, as they will behave differently as we keep on adding explanatory variables. Importantly, we note that the coefficients' signs are in line with the partial derivatives we previously obtained in the model section (i.e., partial derivatives in i), ii), iii), and iv)).

Second, we have relative economic growth as a regressor, in addition to concentration growth (third and fourth columns). For the low concentration group (third column), we have that concentration growth and relative output growth have significant coefficients with the expected signs. In effect, a greater concentration or a greater relative economic growth seems to lead to relative credit growth (i.e., in line with i) and ii)).

We have also pondered productivity growth as an additional regressor (fifth and sixth columns). For the low concentration group, we have that the sign of this coefficient follows that of the model above (i.e., in line with iii)). In particular, more productivity appears to indicate higher relative credit growth. In contrast, it is harder to document a possible effect from relative productivity growth in the case of the high concentration group (sixth column). Moreover, notice that in the group with low concentration, the R^2 now reaches 0.385.

We similarly consider concentration growth and relative wage growth (seventh and eight columns). We observe that relative wage growth has the expected sign in the low concentration case. All else being equal, an increase in wage growth in the relevant sector seems to lead to a decrease in credit growth, as profits decline in tandem. This is in line with the sign of the partial derivative of profits with respect to the price of an input in the model (i.e., in line with iv)).

On the whole, we underscore that in all three cases relative credit growth in the high concentration group seems to be little affected -under these specifications- by changes in relative output, labor productivity, and wage growth rates. These results contrast with the estimations for the low concentration group.

We next consider a specification that combines, in addition to concentration growth, as regressors relative output, productivity, and wage growth rates, in pairs; and, subsequently, all three additional variables (Table 6). We have first pondered relative output and labor productivity growth (first and second columns). For the low concentration group, both coefficients have the expected signs (i.e., in line with ii) and iii)). For the high concentration group, their coefficients seem to be less relevant.

We also have relative output and wage growth rates as additional regressors (third and fourth columns). By the same token, we combine relative labor productivity and wage growth rates (fifth and sixth columns). In both cases, the coefficients associated with the low concentration group have the expected signs (respectively, in line with ii) and iii), and in line with iii) and iv)), but those associated with the high concentration group appear to have a lessened influence.

More generally, we next consider three additional regressors jointly, relative output, labor productivity, and wage growth rates (columns seventh and eighth). Most of our previous results seem to be maintained. For the low concentration group, the coefficients associated with relative output and wage growth rates have the expected signs and are statistically significant (i.e., in line with ii) and iv)). We point out that the coefficient associated with productivity growth, although having the correct sign (i.e., in line with iii)), is not statistically significant. Moreover, the adjusted R^2 is now comparable and even higher than that of the concentrated group panel regression. In contrast, the analogous coefficients associated with the high concentration group do not seem to explain much of the relative credit growth's variability.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0435 (4.37)***	0.171 (13.71)***	0.0537 (5.87)***	0.171 (13.64)***	0.0517 (5.50)***	0.171 (13.65)***	0.0531 (5.81)***	0.171 (13.68)***
Relative Economic Growth	0.0308 (2.02)**	0.123 (1.10)	0.0744 (11.42)***	0.0780 (0.76)			0.0577 (4.02)***	0.124 (1.11)
Relative LPI Growth	0.139 (3.77)***	-0.0931 (-0.96)			0.175 (10.48)***	-0.0613 (-0.67)	0.0468 (1.31)	-0.104 (-1.05)
Relative Wage Growth			-0.405 (-8.31)***	0.120 (0.34)	-0.328 (-6.34)***	0.193 (0.54)	-0.381 (-7.33)***	0.197 (0.55)
Constant	0.0983 (1.64)	-0.0144 (-0.11)	0.0919 (1.69)*	-0.0183 (-0.13)	0.137 (2.47)**	-0.00193 (-0.01)	0.100 (1.84)*	0.000571 (0.00)
N	261	261	261	261	261	261	261	261
R^2	0.395	0.425	0.497	0.423	0.469	0.423	0.501	0.426
adj. R^2	0.383	0.414	0.487	0.412	0.458	0.412	0.489	0.412

Table 6. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent $p<0.1$, $p<0.05$, and $p<0.01$, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

In the case of economic growth, as mentioned, we are somewhat concerned about the possible presence of endogeneity. In effect, while economic growth leads to credit growth, it is plausible that credit growth itself leads to economic growth. To mitigate such a potential issue, we have estimated our panel regressions using lagged economic growth. In general, our key results are maintained, albeit in some cases, its statistical significance changes (Tables 7 and 8). In addition, the coefficient associated with relative productivity growth is statistically significant (i.e., in line with iii)) (Table 8).

As an important remark, we refer to the specification in columns seven and eight, Table 6 or 8, as our main model. This refers to the panel data regression model (in equation 4), without controls, which have been denoted by $\boldsymbol{X_{i,t}}$. Also, the main model can feature contemporaneous or lagged economic growth as a regressor.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0438	0.171	0.0395	0.171	0.0435	0.171	0.0558	0.171
	(3.52)***	(13.69)***	(3.60)***	(13.53)***	(4.35)***	(13.68)***	(4.98)***	(13.65)***
Lagged Relative Economic Growth			0.0698	0.0297				
			(8.83)***	(0.29)				
Relative LPI Growth					0.205	-0.0507		
					(11.88)***	(-0.57)		
Relative Wage Growth							-0.479	0.141
							(-8.08)***	(0.40)
Constant	0.160	-0.0240	0.0825	-0.0308	0.119	-0.0166	0.177	-0.0144
	(2.17)**	(-0.18)	(1.26)	(-0.23)	(2.01)**	(-0.12)	(2.68)***	(-0.11)
N	261	261	258	258	261	261	261	261
R^2	0.046	0.422	0.272	0.421	0.385	0.422	0.240	0.422
adj. R^2	0.035	0.415	0.261	0.412	0.375	0.413	0.228	0.413

Table 7. Panel Data Regressions
Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.
Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0434	0.171	0.0498	0.171	0.0517	0.171	0.0517	0.171
	(4.35)***	(13.54)***	(4.84)***	(13.49)***	(5.50)***	(13.65)***	(5.49)***	(13.50)***
Lagged Relative Economic Growth	0.0225	0.0752	0.0566	0.0232			0.0166	0.0691
	(2.37)**	(0.64)	(7.47)***	(0.22)			(1.85)*	(0.58)
Relative LPI Growth	0.171	-0.0862			0.175	-0.0613	0.152	-0.0917
	(7.54)***	(-0.85)			(10.48)***	(-0.67)	(7.09)***	(-0.89)
Relative Wage Growth			-0.369	0.110	-0.328	0.193	-0.316	0.152
			(-6.60)***	(0.30)	(-6.34)***	(0.54)	(-6.10)***	(0.42)
Constant	0.0971	-0.0203	0.110	-0.0227	0.137	-0.00193	0.119	-0.00843
	(1.63)	(-0.15)	(1.80)*	(-0.16)	(2.47)**	(-0.01)	(2.14)**	(-0.06)
N	258	258	258	258	261	261	258	258
R^2	0.406	0.423	0.380	0.422	0.469	0.423	0.483	0.423
adj. R^2	0.395	0.411	0.367	0.410	0.458	0.412	0.471	0.410

Table 8. Panel Data Regressions.
Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.
Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

In view of these estimations, we would like to underscore that for those sectors in the high concentration group, we do not believe that banks overlook the relative growth, productivity, and wage growth rates. Rather, they pay relatively less attention to them and, thus, it is harder for us econometricians to characterize their relative credit growth as a function of the referred variables.

We would like to point out a broad interpretation about the constant coefficients in these panel regressions. Note that the group with a low concentration tends to have positive and statistical significant constants. In contrast, the high concentration group tends to exhibit constants that are not statistically significant. Thus, if one hypothetically sets all regressors to zero, the low concentration group would have a higher relative credit growth. Nonetheless, by letting the HHI growth rates be different from zero, in the high concentration group, the larger coefficient associated with HHI growth allows such a group to obtain greater increments in relative credit growth.

We next control for the cost of credit in two related ways. In our main model, we include as a regressor the difference between the credit rate of the sector and a weighted average of credit rates of all sectors (Tables 9 and 11). This reflects the relative cost of total credit outstanding. Separately, in our main model, we have included the difference between the marginal credit rate of the sector and a weighted average of marginal credit rates of all sectors. This captures the relative cost of marginal credit. In both cases, their weights are based on the sectors' contributions toward GDP.

	I	II	III	IV	V	VI
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0531 (5.81)***	0.171 (13.68)***	0.0541 (5.96)***	0.143 (11.12)***	0.0553 (5.98)***	0.165 (13.02)***
Relative Economic Growth	0.0577 (4.02)***	0.124 (1.11)	0.0536 (3.74)***	0.0999 (0.94)	0.0567 (3.96)***	0.145 (1.31)
Relative LPI Growth	0.0468 (1.31)	-0.104 (-1.05)	0.0553 (1.55)	-0.115 (-1.22)	0.0486 (1.36)	-0.120 (-1.22)
Relative Wage Growth	-0.381 (-7.33)***	0.197 (0.55)	-0.390 (-7.54)***	0.263 (0.77)	-0.377 (-7.25)***	0.116 (0.33)
Relative Marginal Credit Rate			-0.453 (-2.22)**	-1.747 (-5.48)***		
Relative Credit Rate					-0.800 (-1.50)	-1.066 (-2.44)**
Constant	0.100 (1.84)*	0.000571 (0.00)	0.0477 (0.81)	0.243 (1.76)*	0.0269 (0.37)	-0.0664 (-0.48)
N	261	261	261	261	261	261
R^2	0.501	0.426	0.510	0.487	0.505	0.439
adj. R^2	0.489	0.412	0.496	0.473	0.491	0.424

Table 9. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from INEGI, CNBV, and IMSS.

On these estimations, we have the following comments. First, our key results seem to be maintained. Second, when we include relative credit interest rates, their coefficients are statistically significant and negative for both groups. In effect, higher costs of credit should lead to less relative credit growth, all else being equal. However, when we consider relative marginal costs, while both coefficients are negative, only the coefficient associated with the high concentration group is significant. Still, this result changes when we lag output growth.

Other possible relevant controls are exports and imports real growth rates. In effect, an increase in imports might be associated with a reduction in market concentration in some sectors, while an increase in exports might be indicative of an increase in productivity. These data have some limitations in so far, for instance, imports are aggregated, as mentioned. In addition, evidently, exports are only directly relevant to some specific sectors. In this regard, our groups' division is a natural one, since the group with low concentration is the one more likely to export, while the group with a high concentration is less likely to do so, for known reasons.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0531 (5.81)***	0.171 (13.68)***	0.0526 (5.80)***	0.169 (13.45)***	0.0532 (5.84)***	0.170 (13.56)***	0.0527 (5.81)***	0.169 (13.42)***
Relative Economic Growth	0.0577 (4.02)***	0.124 (1.11)	0.0648 (4.45)***	0.141 (1.26)	0.0645 (4.34)***	0.117 (1.05)	0.0662 (4.46)***	0.135 (1.19)
Relative LPI Growth	0.0468 (1.31)	-0.104 (-1.05)	0.0277 (0.76)	-0.120 (-1.20)	0.0457 (1.28)	-0.0878 (-0.87)	0.0302 (0.82)	-0.110 (-1.07)
Relative Wage Growth	-0.381 (-7.33)***	0.197 (0.55)	-0.370 (-7.13)***	0.119 (0.33)	-0.441 (-7.01)***	0.121 (0.33)	-0.393 (-5.66)***	0.0980 (0.27)
Imports Growth			-0.0362 (-2.24)**	0.0534 (1.32)			-0.0307 (-1.57)	0.0448 (0.97)
Exports Growth					-0.0164 (-1.67)*	0.0315 (0.98)	-0.00603 (-0.51)	0.0141 (0.38)
Constant	0.100 (1.84)*	0.000571 (0.00)	0.134 (2.39)**	-0.0581 (-0.40)	0.126 (2.23)**	-0.0449 (-0.31)	0.138 (2.43)**	-0.0690 (-0.47)
N	261	261	261	261	261	261	261	261
R^2	0.501	0.426	0.510	0.430	0.506	0.428	0.511	0.430
adj. R^2	0.489	0.412	0.497	0.414	0.492	0.412	0.495	0.412

Table 10. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

All in all, controlling for exports and imports does not seem to notably affect our previous results (Table 10). In two cases, the coefficients associated with these controls are statistically significant. For the low concentration group (third column), an increase in imports has a negative effect on credit growth. We hypothesize that such an increase adversely affects their concentration and, accordingly, their profits and credit. For the low concentration group (fifth column), an increase in exports leads to a decrease in relative credit growth. Although the interpretation of this result is not evident, it could very well point to the fact that exporting firms possibly have a wider array of choices for their financing.

As we have previously done, we lag economic growth to mitigate the possible presence of endogeneity. First, we estimate the main model controlling for the cost of credit, having economic growth lagged (Table 11). Second, we estimate the main model controlling for exports and imports' real growth, having economic growth lagged (Table 12).

In the first case, when we control for the cost of credit, we have that two coefficients' statistical significance changes. For the low concentration group (fifth column), the coefficients associated with relative labor productivity growth and with relative credit rate are, in this case, statistically significant and have the expected sign. Interestingly enough, the coefficients associated with the credit rate have similar magnitudes in both groups. Thus, our previous results seem to be maintained when controlling for the cost of credit.

In the second case, when we control for exports and imports, and use lagged economic growth as a regressor, we have that these controls are not statistically significant (Table 12). Again, we think that these results should not be interpreted as if such controls are irrelevant. Rather, given the diverse effects they might have depending on the sector in question and the lack of more granular data, it is problematic to measure their effects in a more accurate way.

	I	II	III	IV	V	VI
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0517 (5.49)***	0.171 (13.50)***	0.0530 (5.67)***	0.143 (10.97)***	0.0548 (5.75)***	0.164 (12.77)***
Lagged Relative Economic Growth	0.0166 (1.85)*	0.0691 (0.58)	0.0158 (1.79)*	0.0536 (0.48)	0.0157 (1.76)*	0.0893 (0.76)
Relative LPI Growth	0.152 (7.09)***	-0.0917 (-0.89)	0.152 (7.16)***	-0.101 (-1.04)	0.153 (7.17)***	-0.105 (-1.03)
Relative Wage Growth	-0.316 (-6.10)***	0.152 (0.42)	-0.330 (-6.40)***	0.235 (0.68)	-0.312 (-6.05)***	0.0737 (0.20)
Relative Marginal Credit Rate			-0.505 (-2.41)**	-1.758 (-5.45)***		
Relative Credit Rate					-1.006 (-1.78)*	-1.046 (-2.35)**
Constant	0.119 (2.14)**	-0.00843 (-0.06)	0.0571 (0.94)	0.241 (1.72)*	0.0250 (0.33)	-0.0709 (-0.50)
N	258	258	258	258	258	258
R^2	0.483	0.423	0.495	0.485	0.490	0.436
adj. R^2	0.471	0.410	0.481	0.470	0.475	0.420

Table 11. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0517 (5.49)***	0.171 (13.50)***	0.0517 (5.49)***	0.169 (13.23)***	0.0517 (5.46)***	0.170 (13.36)***	0.0512 (5.41)***	0.168 (13.19)***
Lagged Relative Economic Growth	0.0166 (1.85)*	0.0691 (0.58)	0.0146 (1.59)	0.0952 (0.79)	0.0168 (1.66)*	0.0781 (0.66)	0.0175 (1.73)*	0.0946 (0.79)
Relative LPI Growth	0.152 (7.09)***	-0.0917 (-0.89)	0.154 (7.14)***	-0.111 (-1.07)	0.151 (5.53)***	-0.0789 (-0.76)	0.141 (4.88)***	-0.0996 (-0.94)
Relative Wage Growth	-0.316 (-6.10)***	0.152 (0.42)	-0.309 (-5.92)***	0.0700 (0.19)	-0.314 (-4.85)***	0.0714 (0.19)	-0.274 (-3.74)***	0.0430 (0.11)
Imports Growth			-0.0157 (-0.94)	0.0521 (1.27)			-0.0234 (-1.16)	0.0411 (0.88)
Exports Growth					0.000626 (0.06)	0.0339 (1.04)	0.00922 (0.69)	0.0186 (0.50)
Constant	0.119 (2.14)**	-0.00843 (-0.06)	0.137 (2.32)**	-0.0642 (-0.44)	0.118 (1.95)*	-0.0554 (-0.38)	0.126 (2.08)**	-0.0782 (-0.52)
N	258	258	258	258	258	258	258	258
R^2	0.483	0.423	0.485	0.427	0.483	0.426	0.486	0.428
adj. R^2	0.471	0.410	0.471	0.411	0.469	0.410	0.469	0.409

Table 12. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

Cross-terms might be pertinent in this context. Analytically, whether in fact they are depends on the profit function's being additive separable with respect to the variables of interest. In any case, we consider three cross-terms: productivity-growth, productivity-concentration, and concentration-growth. We highlight three empirical findings. First, we underscore that our main results are maintained (Table 13). As in other cases, while some regressors might not be statistically significant, they tend to become statistically significant once we use lagged economic growth (Table 14).

Second, in the first and seventh columns of Table 14, we have that the productivity and growth cross-terms are positive and statistically significant. This is intuitive, since at a sectorial level, higher productivity impacts positively how growth affects credit and vice versa. Yet, one needs to point out the small magnitudes of both coefficients.

Third, in columns four and eight, in the case of the high concentration group, we have that the productivity-concentration term is positive and statistically significant. This means that, at the margin, an increase in concentration positively affects the impact that relative productivity growth has on relative credit growth.

These results do not seem to be particularly sensitive when we consider lagged output (Table 14). On the contrary, some variables gain statistical significance, in particular, the labor productivity index (seventh column).

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0542 (5.95)***	0.171 (13.62)***	0.0540 (5.85)***	0.173 (14.18)***	0.0531 (5.80)***	0.170 (13.32)***	0.0563 (5.95)***	0.169 (13.61)***
Relative Economic Growth	0.0475 (3.13)***	0.157 (1.29)	0.0586 (4.07)***	0.0993 (0.91)	0.0591 (3.99)***	0.118 (1.05)	0.0460 (2.86)***	0.116 (0.98)
Relative LPI Growth	0.0550 (1.53)	-0.0908 (-0.90)	0.0473 (1.32)	-0.0820 (-0.85)	0.0446 (1.23)	-0.100 (-1.01)	0.0612 (1.62)	-0.0512 (-0.52)
Relative Wage Growth	-0.341 (-6.11)***	0.189 (0.53)	-0.387 (-7.35)***	0.221 (0.63)	-0.387 (-7.17)***	0.204 (0.57)	-0.340 (-5.85)***	0.241 (0.69)
Cross IPL x IGAE	0.00256 (1.92)*	0.0419 (0.71)					0.00261 (1.95)*	0.0499 (0.86)
Cross IPL x HHI			0.00255 (0.73)	0.0622 (3.75)***			0.00572 (0.81)	0.0678 (3.98)***
Cross HHI x IGAE					0.000578 (0.40)	-0.00882 (-0.42)	-0.00134 (-0.46)	-0.0306 (-1.43)
Constant	0.0422 (0.68)	-0.0361 (-0.24)	0.0993 (1.82)*	-0.0547 (-0.40)	0.0992 (1.81)*	0.00204 (0.01)	0.0412 (0.66)	-0.0983 (-0.68)
N	261	261	261	261	261	261	261	261
R^2	0.508	0.427	0.502	0.456	0.501	0.426	0.509	0.462
adj. R^2	0.494	0.411	0.488	0.441	0.487	0.410	0.492	0.442

Table 13. Panel Data Regressions

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

	I	II	III	IV	V	VI	VII	VIII
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0544 (5.87)***	0.171 (13.45)***	0.0519 (5.45)***	0.174 (14.08)***	0.0516 (5.48)***	0.169 (13.13)***	0.0571 (5.98)***	0.170 (13.52)***
Lagged Relative Economic Growth	0.0164 (1.88)*	0.0673 (0.57)	0.0165 (1.84)*	0.0958 (0.83)	0.0172 (1.91)*	0.0679 (0.57)	0.0173 (1.96)*	0.0905 (0.78)
Relative LPI Growth	0.129 (5.81)***	-0.0847 (-0.78)	0.153 (6.96)***	-0.0914 (-0.91)	0.149 (6.81)***	-0.0890 (-0.86)	0.130 (5.79)***	-0.0664 (-0.62)
Relative Wage Growth	-0.263 (-4.97)***	0.151 (0.41)	-0.317 (-6.05)***	0.148 (0.42)	-0.308 (-5.81)***	0.163 (0.45)	-0.257 (-4.77)***	0.176 (0.49)
Cross IPL x IGAE	0.00431 (3.40)***	0.0108 (0.19)					0.00412 (3.20)***	0.0264 (0.48)
Cross IPL x HHI			0.000477 (0.13)	0.0661 (3.93)***			0.00853 (1.22)	0.0720 (4.17)***
Cross HHI x IGAE					-0.00101 (-0.71)	-0.0113 (-0.53)	-0.00335 (-1.18)	-0.0324 (-1.51)
Constant	0.00878 (0.14)	-0.0181 (-0.12)	0.119 (2.13)**	-0.0746 (-0.54)	0.119 (2.13)**	-0.00621 (-0.04)	0.0133 (0.21)	-0.0979 (-0.67)
N	258	258	258	258	258	258	258	258
R^2	0.506	0.423	0.483	0.457	0.484	0.424	0.509	0.462
adj. R^2	0.492	0.407	0.469	0.442	0.470	0.408	0.491	0.442

Table 14. Panel Data Regressions: Do Cross-Terms Matter?

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

It is evident that the C&T sector has a level of concentration way beyond other sectors, whereas the rest has more similar levels. Thus, a natural exercise is to exclude the referred sector from the panel regressions. We are then left with five sectors, which we similarly divide in terms of their average concentration level. The group with low concentration is exactly the same as before, whereas the group with high average concentration excludes C&T, retaining the rest of its original sectors. We present the respective estimations in Table 15. The panel regressions with the original groups are in the first, second, and third columns, and the panel regression with the newly defined high concentration group is in the fourth column.

Two general remarks are in order. First, while relative economic growth and productivity growth (with apparently the wrong sign) seem to gain statistical significance for the group with high concentration (Table 15), they do not maintain it in the case of the panel regression that has lagged economic growth (Table 16). Thus, our previous results seem in general to hold.

Second, we observe a drop in the adjusted R^2 in the case of the group with high concentration but excluding the C&T sector. This indicates that much of the variability explained in the original high concentration group is being driven by the referred sector, and understandably so, since it shows the highest concentration.

	I	II	III	IV
	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0531 (5.81)***	0.171 (13.68)***	0.0531 (5.81)***	0.134 (5.89)***
Relative Economic Growth	0.0577 (4.02)***	0.124 (1.11)	0.0577 (4.02)***	0.0909 (1.80)*
Relative LPI Growth	0.0468 (1.31)	-0.104 (-1.05)	0.0468 (1.31)	-0.0866 (-1.91)*
Relative Wage Growth	-0.381 (-7.33)***	0.197 (0.55)	-0.381 (-7.33)***	-0.195 (-1.22)
Constant	0.100 (1.84)*	0.000571 (0.00)	0.100 (1.84)*	-0.0619 (-0.90)
N	261	261	261	174
R^2	0.501	0.426	0.501	0.193
adj. R^2	0.489	0.412	0.489	0.169

Table 15. Panel Data Regressions: Excluding the Communications and Transportation Sector

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively. Columns I and II have the original estimates. Thus, I = III. Column IV excludes the communications and transportation sector.

Source: Estimations with data from *INEGI*, *CNBV*, and IMSS.

	I	II	III	IV
	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0517 (5.49)***	0.171 (13.50)***	0.0517 (5.49)***	0.133 (5.77)***
Lagged Relative Economic Growth	0.0166 (1.85)*	0.0691 (0.58)	0.0166 (1.85)*	0.0183 (0.34)
Relative LPI Growth	0.152 (7.09)***	-0.0917 (-0.89)	0.152 (7.09)***	-0.0611 (-1.30)
Relative Wage Growth	-0.316 (-6.10)***	0.152 (0.42)	-0.316 (-6.10)***	-0.221 (-1.34)
Constant	0.119 (2.14)**	-0.00843 (-0.06)	0.119 (2.14)**	-0.0785 (-1.12)
N	258	258	258	172
R^2	0.483	0.423	0.483	0.183
adj. R^2	0.471	0.410	0.471	0.159

Table 16. Panel Data Regressions: Excluding the Communications and Transportation Sector

Notes: T-statistics in parentheses. *, ** and *** represent $p<0.1$, $p<0.05$, and $p<0.01$, respectively. Columns I and II have the original estimates. Thus, I = III. Column IV excludes the communications and transportation sector.

Source: Estimations with data from *INEGI*, *CNBV*, and *IMSS*.

6. Concentration and Credit Dynamics

We have mentioned the possible presence of counterproductive dynamics between concentration and credit growth. In effect, more concentration can lead to more credit growth and more credit growth to more concentration. To empirically explore this issue, we estimate several panel VARs (PVARs) with the following variables.[23] As endogenous ones, we have concentration growth and relative credit growth. As exogenous variables, we have relative wage, productivity, and output growth rates. Having such variables as exogenous has as an implication that their order in the VARs is not relevant for identification purposes.

For the identification of shocks, we use the Cholesky decomposition, assuming that concentration growth does not respond contemporaneously to a relative credit growth shock.[24] This is plausible given that concentration should depend on a wider array of structural factors. Thus, we estimate a PVAR with the group with low average concentration, and we estimate another PVAR with the group with high average

[23] We use the Stata code provided by Abrigo and Love (2015).

[24] We have also estimated the associated impulse response functions assuming the reverse order, i.e., assuming that relative credit growth does not respond contemporaneously to a concentration growth shock. All except one function have the same responses. The exception is the response of relative credit growth to a concentration growth impulse for the group with high concentration. It has the correct sign but it is statistically significant at a 75% confidence level.

concentration. We use one lag for the PVAR, in line with the Bayesian Information Criteria model selection criterion (see Abrigo and Love, 2015). Such a lag also maintains this setup as close as possible to our previous models. As instruments, we use the same set of variables lagged one to three periods.

We observe that in the group with low concentration, a shock on concentration growth leads to a positive response by relative credit growth (Figure 4). This is as anticipated, based on our previous estimations. On the other hand, a shock on relative credit growth does not lead to a significant response by concentration growth. In fact, the response and associated confidence interval provide no clues about a potential response.

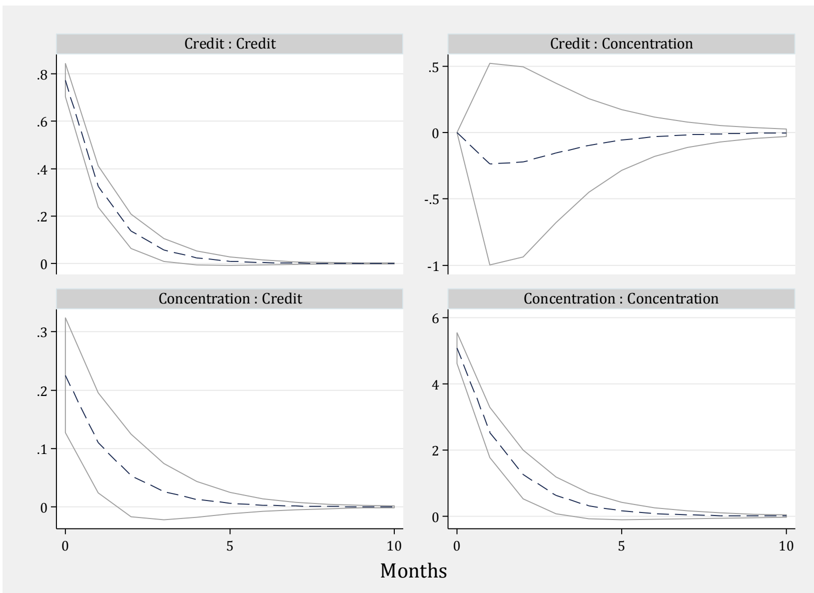

Figure 4. Impulse-Response Functions for the PVAR
Notes: For the estimation of these PVAR only the time series associated with the sectors with low concentration have been used. As endogenous variables, we have concentration growth and relative credit growth. As exogenous variables, we have relative wage, productivity, and economic growth rates. For identification, we use the Cholesky decomposition and assume that concentration growth does not respond contemporaneously to a credit growth shock. We use the same variables lagged one to three periods as instruments. Intervals are at a 95% confidence level.
Source: With data from *INEGI*, *CNBV*, and *IMSS*.

In the case of the group with high concentration (Figure 5), we find that a shock on concentration growth implies a positive response from relative credit growth. Moreover, its response is notably greater than the one from the group of sectors with low concentration (Figure 4).[25]

[25] We have compared two responses obtained from two different PVARs. Evidently, each response depends on its associated impulse. Yet, such responses are broadly comparable since the size of each impulse corresponds to its standard deviation.

Additionally, in the group with high concentration, the response from concentration growth to a shock on relative credit growth is positive and statistically significant. These provide empirical support to the potential presence of counterproductive dynamics between these variables. Feedback dynamics might be taking place that could be detrimental to the allocation of credit, since potential costs could be building up.

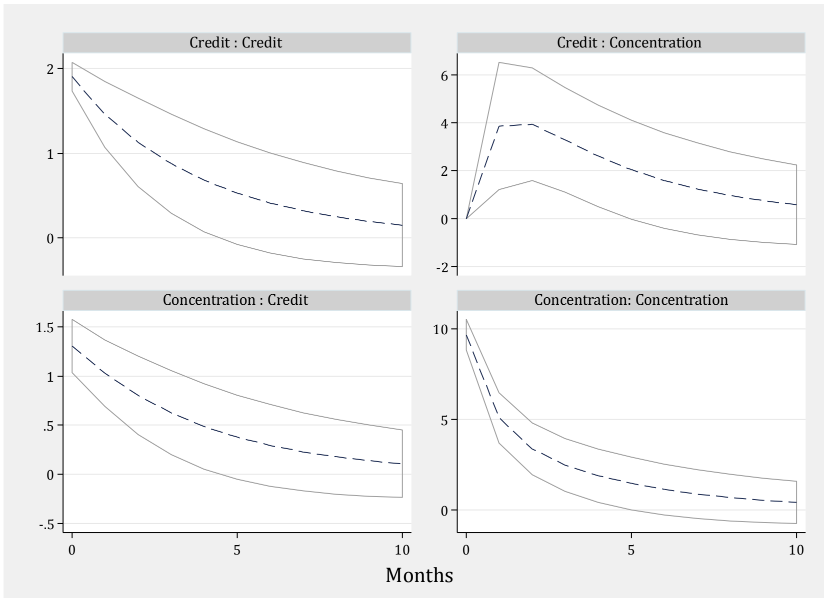

Figure 5. Impulse-Response Functions for the PVAR
Notes: For the estimation of these PVAR only the time series associated with the sectors with high concentration have been used. As endogenous variables, we have concentration growth and relative credit growth. As exogenous variables, we have relative wage, productivity, and economic growth rates. For identification, we use the Cholesky decomposition, and assume that concentration growth does not respond contemporaneously to a relative credit growth shock. We use the same variables lagged one to three periods as instruments. Intervals are at a 95% confidence level.
Source: With data from *INEGI*, *CNBV*, and *IMSS*.

Although we have somewhat simplified our identification approach by including three of our variables as exogenous, we think that these results provide some support to the possible existence of a feedback mechanism. Such a mechanism could be leading, among others, to a relatively higher concentration than otherwise, with the concomitant adverse effects on the economy.

7. Final Remarks

We have documented that relative growth in sectorial concentration, measured with a Herfindahl-Hirschman Index of bank credit, seems to explain relative credit growth in two groups of sectors. However, it appears to explain only a small portion of the relative credit growth's variability in the group with low average concentration. What is more, we have found evidence suggesting that relative labor productivity, output, and wage growth rates can contribute more meaningfully to explain the variability of relative credit growth in the group with low average concentration.

Somewhat surprised, we find that such factors appear to have a less meaningful contribution to explain the relative credit growth's variability in the group with the high average concentration. This should not be interpreted as if these features are irrelevant for their credit allocation. We believe that having a harder time characterizing relative credit growth as function of such factors just lessens their relative importance.

If, as we seem to have found some evidence on, sectors with high levels of concentration tend to obtain a higher proportion of financial resources with less regard to key features, such as their relative productivity growth, then counterproductive dynamics might be taking place. Firms that are concentrated, maintain more credit growth and vice versa. Similarly, some potentially productive firms might be lacking financial resources partially because of their lack of concentration. While they might be able to subsist, the scale and scope of their economic activities can be hampered given the absence of more credit.

As mentioned, these results suggest that, first, from the socially optimal point of view there might be more credit being allocated to less productive sectors.[26] In effect, the more concentrated sectors could be producing less than what is socially optimal. In addition, they are possibly getting a share of the credit that could had been allocated to less concentrated sectors, had there been less concentration in the economy.

Second, these dynamics could partially be explained if verifying the feasibility of allocating a unit credit and monitoring the associated project is less costly in a concentrated sector.

Third, banks that lend to those firms with higher market power might to an extent be able to obtain some benefits from the firms' extraordinary profits.[27] Of course, banks cannot benefit directly from firms' extraordinary profits. To begin with, they face some competition and firms can opt for other sources of credit. Thus, there are limits to such benefits. Still, firms with market power probably have stronger balance sheets and stable profits, features that banks prefer when lending firms credit, all else being equal. In addition, these mechanisms could lead to the possible presence of counterproductive dynamics between concentration and credit. We have provided some empirical support to that effect.

[26] As said, firms with market power tend to have, for example, strong balance sheets, one among other features that banks would consider when allocating their credit.

[27] As mentioned, banks cannot benefit directly from firms' extraordinary profits. Evidently, they face some competition and firms can opt for other sources of credit. Thus, there are limits to the referred benefits.

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Appendix

A1. Variations to Panel Data Estimations and Further Controls

We have checked on a number of variations and other controls in our estimations, as we describe next. First, we have used the second type of measurement of labor productivity, instead of the first one. As mentioned, it is not available for all of the sectors we have considered. Our previous results are in general maintained.

Second, as described, we have used relative growth rates, which account for common shocks on growth rates. In addition, we have also estimated the main model with fixed-time effects lasting one year and, separately, lasting six months. In our main model, none of their associated coefficients appear to be statistically significant. We could have considered fixed time effects lasting three months, but these would have been hard to tell apart from the seasonal variations in some of our time series.

Third, a natural issue is whether these results hold when we control for exchange rates. In effect, variations in the exchange rate might have an impact on the competitiveness of certain sectors. To explore such a possibility, we control for the nominal and the real exchange rate on separate panel data regressions (Tables A1 and A2). For comparison, we have included the regressions without these controls. Neither the nominal nor the real exchange rate seem to have an evident effect.

	I	II	III	IV	V	VI
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0531 (5.81)***	0.171 (13.68)***	0.0529 (5.73)***	0.171 (13.64)***	0.0534 (5.79)***	0.171 (13.66)***
Relative Economic Growth	0.0577 (4.02)***	0.124 (1.11)	0.0578 (3.99)***	0.121 (1.08)	0.0572 (3.96)***	0.119 (1.07)
Relative LPI Growth	0.0468 (1.31)	-0.104 (-1.05)	0.0462 (1.27)	-0.128 (-1.23)	0.0481 (1.33)	-0.147 (-1.42)
Relative Wage Growth	-0.381 (-7.33)***	0.197 (0.55)	-0.382 (-7.31)***	0.232 (0.64)	-0.379 (-7.18)***	0.262 (0.72)
Exchange Rate Growth			0.00335 (0.10)	0.0713 (0.79)		
Real Exchange Rate Growth					0.0126 (0.31)	-0.144 (-1.36)
Constant	0.100 (1.84)*	0.000571 (0.00)	0.0986 (1.71)*	-0.0288 (-0.20)	0.103 (1.86)*	-0.0205 (-0.15)
N	261	261	261	261	261	261
R^2	0.501	0.426	0.501	0.427	0.501	0.430
adj. R^2	0.489	0.412	0.487	0.411	0.487	0.414

Table A1. Panel Data Regressions.

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI*, *CNBV*, *IMSS*, *Banco de México*, and BIS.

Fourth, in our exercises, we have opted for the estimation of separate panel data regressions, as extensively explained. An alternative is to estimate a panel data regression with all sectors, in which a dummy variable distinguishes between the coefficients of the low and high concentration groups. Thus, we explore if such a model leads to different coefficients measuring the impact of concentration growth on relative credit growth. More concretely, for instance, consider the following panel data regression:

$$c_{i,t} = \beta_0 + D_i\beta_{1,L}hhi_{i,t} + (1 - D_i)\beta_{2,H}hhi_{i,t} + \epsilon_{i,t}$$

where we let $D_i = 1$ if the data point is from a sector in the low concentration group, and let $D_i = 0$ if the data point is from a sector in the high concentration group. Thus, $\beta_{1,L}$ measures the impact of concentration growth on relative credit growth for the low concentration group, and $\beta_{2,H}$ measures the same impact but for the high concentration group. This approach could have as an advantage an improvement in the estimators' precision. As one drawback, we cannot compare statistics across the two sets of panel data regressors; e.g., between the R^2s.

We have then estimated one panel data regression considering all six sectors but including one dummy variable. We note that we only consider a differentiated effect for concentration growth. Having estimated our panel regression as in Table 5, we observe that the coefficients associated with concentration growth are essentially the same as in the separate regressions cases.

Fifth, as explained, the HHI has been constructed based on credit data. There is then the possibility of the presence of endogeneity when using HHI growth as a regressor. Thus, we have estimated our panel regressions as in Table 5, but lagging the HHI growth one month. Our main results are in general maintained and, in a number of cases, the contrast between the high and low concentration group sharpens.

	I	II	III	IV	V	VI
	Low Concentration	High Concentration	Low Concentration	High Concentration	Low Concentration	High Concentration
HHI Growth	0.0517 (5.49)***	0.171 (13.50)***	0.0522 (5.49)***	0.171 (13.47)***	0.0526 (5.53)***	0.170 (13.48)***
Lagged Relative Economic Growth	0.0166 (1.85)*	0.0691 (0.58)	0.0165 (1.85)*	0.0674 (0.57)	0.0165 (1.84)*	0.0781 (0.66)
Relative LPI Growth	0.152 (7.09)***	-0.0917 (-0.89)	0.153 (7.09)***	-0.119 (-1.10)	0.153 (7.11)***	-0.144 (-1.32)
Relative Wage Growth	-0.316 (-6.10)***	0.152 (0.42)	-0.315 (-6.08)***	0.189 (0.51)	-0.311 (-5.95)***	0.216 (0.59)
Exchange Rate Growth			-0.0151 (-0.43)	0.0779 (0.85)		
Real Exchange Rate Growth					0.0287 (0.70)	-0.154 (-1.44)
Constant	0.119 (2.14)**	-0.00843 (-0.06)	0.127 (2.16)**	-0.0417 (-0.29)	0.125 (2.22)**	-0.0317 (-0.23)
N	258	258	258	258	258	258
R^2	0.483	0.423	0.484	0.425	0.484	0.428
adj. R^2	0.471	0.410	0.469	0.409	0.470	0.412

Table A2. Panel Data Regressions.

Notes: T-statistics in parentheses. *, ** and *** represent p<0.1, p<0.05, and p<0.01, respectively.

Source: Estimations with data from *INEGI, CNBV, IMSS,* Banco de México, and BIS.

Six, we have controlled for global variables that might affect local credit. Specifically, we have considered the Federal Funds Rate, the Wu and Xia rate (2015), the Krippner (2013) rate, and Lombard and Zhu (2014) rate, and average of the last three shadow rates, and the Bank of England Official Rate. We estimate the main model having each of these variables, separately, as controls. For all, their associated coefficients are negative, as expected. A higher interest rate leads to a lower growth of credit, all else being constant. Yet, except for the Krippner rate, they are not statistically significant. There are at least two measurements issues in this context. One, not all firms have direct access to financing abroad. Two, the extent to which these rates are able to capture the price of relative credit.

Seventh, we have focused on month-to-month growth rates in all variables. This was done for two reasons. First, the shorter the growth rates' horizon is, the less factors come into play in the determination of the dependent variable and, thus, the less variables one needs to consider as regressors. Second, data availability has allowed us to ponder month-to-month growth rates. Still, we also briefly consider quarterly and semiannual growth rates, as we explain next.

For the quarterly growth rates, the panel regressions with only the HHI growth as a regressor have an adjusted R^2 for the low concentration group of 0.04 and of 0.56 for the high concentration group. The results with one additional regression hold in that, separately, relative output, labor productivity, and wage growth rates are statistically significant in the group with low concentration, and are not in the group with high concentration.

For the semiannual growth rates, the panel regressions with only the HHI growth as a regressor have an adjusted R^2 for the low concentration group of 0.04, and of 0.68 for the high concentration group. The results with one additional regression hold in that, separately, relative economic, labor productivity, and wage growth rates are statistically significant in the group with low concentration, and are not in the group with high concentration. In addition, the regression with all four variables (HHI growth, relative economic, labor productivity, and wage growth rates) have, for example, in both groups a negative coefficient for labor productivity growth. This suggests there might be model misspecification. In general, the longer growth rate horizons for the dependent variable are, the more factors one needs to consider as regressors.

Finally, during our sample period, the implementation of the Financial and Competition Reforms started in 2014. Thus, one could ask if there are any apparent effects in our credit data or whether they could have any impact on our estimations. Arguably, since our credit data finish in December 2016, it is relatively early to assess whether the referred reforms have had an effect. In addition, since we have also estimated the panel regression with time fixed effects that last for a year, they could have captured a possible initial effect in the relative growth rates. Yet, there was no apparent evidence, but again, we think it is too early to tell.

A2. Ballpark Calculations on Relative Credit Growth

We present some ballpark calculations to compare how relative credit growth changes after a one standard increase in each of the regressors that have a statistically significant coefficient, separately, in each group of sectors. For the high concentration group, a one standard deviation increment in HHI growth corresponds to an increase in relative credit growth of 1.78 percentage points. On the other hand, for the low concentration group, we have that a one standard deviation increment in the HHI growth leads to a 0.41 rise in relative credit growth.

Accordingly, in the low concentration group, it would take a 4.3 standard deviation increase in its HHI growth to obtain an increase of 1.78 percentage points in relative credit growth. Similarly, one standard deviation increments in relative growth in LPI, (lagged) output, and wage, would lead, respectively, to a 0.64, 0.25 and -0.23 increase in relative credit growth. Hence, it would take 2.8, 7.1, and -7.7 standard deviation changes, respectively, to obtain an increase in 1.78 percentage points in relative credit growth (Table A3).

All in all, while these approximations overlook possible correlations between such variables, can entail some aggregation bias (given that they are based on the panel regressions), and reemphasizing that the panel regressions account only for approximately 0.5 and 0.4 of the credit growth variability, respectively, we nonetheless think they illustrate the potential trade-offs in the allocation of credit. In sum, they are revealing about the relative costs in terms of the factors that seem to be determining relative credit growth among these groups of sectors.

	$X \to X + \hat{\sigma}_X$			
A one standard deviation change in:	**HHI Growth**	**LPI Relative Growth**	**Lagged IGAE Relative Growth**	**Wage Relative Growth**
Relative credit growth in the **high** concentration group given a one standard deviation change in:	1.78	-	-	-
Relative credit growth in the **low** concentration group given a one standard deviation change in:	0.41	0.64	0.25	-0.23

Table A3. Relative Credit Growth
Notes: Change in relative credit growth in each group (i.e., high and low concentration) under a change in one standard deviation of the respective variable: HHI growth, relative LPI growth, lagged relative IGAE growth, and relative wage growth.
Source: Estimations with data from *INEGI, CNBV,* and *IMSS.*

Variable/Sector	Agricultural	Commercial	Communications and Transportation (C&T)	Construction	Industrial (Manufacturing)	Services (Non-financial)	Total
HHI	Direct	Direct	Direct	Direct	Direct	Direct	-------
Credit	Direct	Direct	Direct	Direct	Direct	Direct	Aggregated (Aggregating sectors)
Credit Rates	Direct	Direct	Direct	Direct	Direct	Direct	Weighted average based on sectorial GDP contributions as weights (Aggregating sectors)
Labor Productivity (LPI)[1/]	Approximated by Primary Activities	Simple average	Weighted average based on sub-sectorial GDP contributions as weight[7/]	Direct	Direct	Direct	Direct (Economy indicator)
Economic Growth (IGAE)[2/]	Approximated by Primary Activities	Direct	Direct	Direct	Direct	Weighted average based on sub-sectorial GDP contributions as weights[7/]	Direct (Economy indicator)
Wages[3/]	Approximated by Primary Activities	Direct	Direct	Direct	Approximated by Transformation Industry.	Direct	Direct (Economy indicator)
Imports[4/]	-------	-------	-------	-------	-------	-------	Direct (Economy indicator)
Exports[4/]	Direct	Economy indicator	Economy indicator	Economy indicator	Direct	Direct	Direct (Economy indicator)
Exchange Rates (nominal[5/] and real[6/])	-------	-------	-------	-------	-------	-------	Direct

Table A4. Aggregation/Matching Method

Notes:

1/Source: *INEGI*.
2/Source: *INEGI*.
3/*Salario Diario Asociado a Trabajadores Asegurados en el IMSS por Sector de Actividad Económica.* Source: *IMSS*.
4/In Mexican pesos (we use monthly average MXN/USD exchange rate), deflated using the CPI.
5/Source: Banco de México.
6/Source: BIS, broad index.
7/To construct these variables, we first calculate the cited weighted average, and then we take their monthly growth rates.