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Banking sector concentration, credit shocks and aggregate fluctuations☆

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ABSTRACT

This paper studies whether the raise in concentration experienced by the Spanish banking sector has lead to the increase of bank-specific credit shocks contribution to aggregate credit. We decompose aggregate credit volatility and find that (i) the Spanish banking sector is granular, (ii) the direct effect of bank-specific shocks accounts for the overwhelming majority of the variation in aggregate volatility, contrary to the manufacturing sector, and (iii) the raise in concentration translated into an increase of bank-specific shocks contribution to aggregate volatility.

1. Introduction

During the Spanish real estate boom, the saving banks (*Cajas de Ahorro*) rapidly gained market share from commercial banks thanks to indiscriminate lending to real estate developers. When the global financial crisis hit Spain, the construction bubble burst and the *Cajas* – that accounted for more than half of the banking sector – collapse, thus compromising the stability of the financial system.[1] Aiming to avoid the collapse of the entire system, the Spanish government decided to create the Fund for Orderly Restructuring of Banks (*Fondo de Reestructuración Ordenada Bancaria*, FROB), which consisted mainly of a process of mergers and acquisitions that rapidly increased concentration in the banking sector (see Fig. 1).

Recently, Gabaix (2011)'s *granular hypothesis* argues that, in the presence of sufficiently large concentration, idiosyncratic shocks to large firms may translate into sizable aggregate fluctuations.[2] In light of the increase in the concentration experienced by

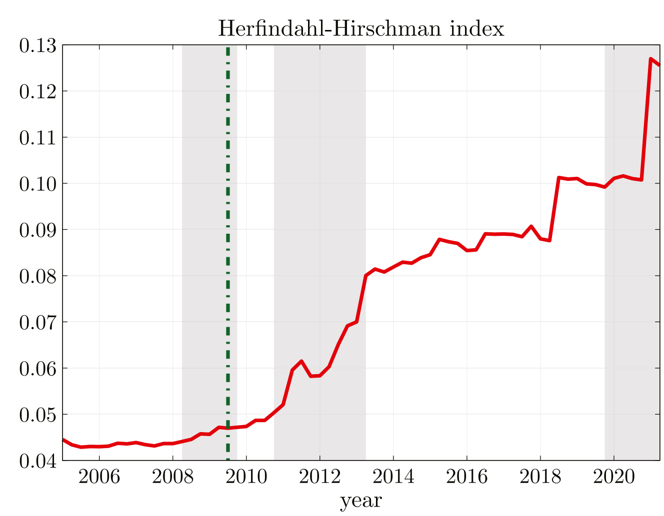

Fig. 1. Concentration in the Spanish banking sector. **Notes**: We measure concentration using the Herfindahl–Hirschman index of credits. Shaded lines indicate recession dates reported by the Spanish Economic Association data. The vertical line marks the creation of the FROB.

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1 Fernandez-Villaverde et al. (2013) and Royo (2013) discuss, respectively, the causes and consequences of the collapse of the *Cajas*.

2 Excluding the banking sector, Blanco-Arroyo et al. (2018) find that the Spanish economy is granular.

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the Spanish banking sector, this paper seeks to evaluate whether the contribution of bank-specific credit shocks to aggregate credit fluctuations has increased. We study credit shocks because of the key role they play in the transmission of granular effects from the banking sector to aggregate investment and output (Bremus et al., 2018; Amiti and Weinstein, 2018).

Using a dataset that covers the quasi-census of Spanish credit institutions, we decompose aggregate credit volatility following di Giovanni et al. (2014)'s identification strategy and find that the contribution of bank-specific credit shocks to aggregate credit fluctuations has increased dramatically since the restructuring process began. The rise has been mainly driven by the direct effect of bank-specific shocks, which, in turn, heavily depends on the degree of concentration. This is in contrast to the widely studied manufacturing sector, in which firms linkages are the responsible for the amplification of firm-specific shocks. Therefore, our results suggest that these two crucial sectors in the economy have different propagation mechanisms of specific shocks.

Our paper builds on the literature on the granular origins of business cycle fluctuations (see, e.g., Gabaix, 2011; di Giovanni et al., 2014) and relates to the strand of the literature that studies the effect on bank heterogeneity on aggregate outcomes (Buch and Neugebauer, 2011; Bremus et al., 2018; Amiti and Weinstein, 2018; Alfaro et al., 2021).

2. Data

Quarterly unconsolidated domestic credit data at the bank-level comes from *Asociación Española de Bancos* (AEB), *Confederación Española de Cajas de Ahorro* (CECA) and *Unión Nacional de Cooperativas de Crédito* (UNACC). Our dataset covers the quasi-census of Spanish credit institutions during the period 2005:I-2021:II.[3] We mitigate the impact of outliers by winsorizing growth rates at the 3 and the 97 percentile.[4]

Yearly value of unconsolidated sales data at the firm-level comes from *Sistema de Análisis de Balances Ibéricos* (SABI) database, which is compiled by Bureau Van Dijk Electronic Publishing (BvD). The dataset covers 135.000 Spanish manufacturing firms during the period 2004–2020.[5] To ensure comparability, we use the same winsorizing cut-off as for banks.

Credits and sales are deflated using the GDP deflator from *Eurostat* database.

3. Methodology

Total aggregate credit c_t in year t is given by $c_t = \sum_i c_{it}$, where c_{it} is defined as the credit lended by bank i in year t. The growth rate of aggregate credit is then defined as $g_{\mathcal{A}t} = c_t/c_{t-1} - 1$. We can express $g_{\mathcal{A}t}$ as the weighted sum of the credit growth rates of each individual bank g_{it}:

$$g_{\mathcal{A}t} = \sum_i w_{it-1} g_{it}, \tag{1}$$

where the weights w_{it-1} denote bank i's credit share in aggregate credit (i.e., $w_{it-1} = c_{it-1}/c_{t-1}$). Following the convention in the literature (e.g., Buch and Neugebauer, 2011; Bremus et al., 2018; Alfaro et al., 2021), we breakdown bank's growth rate into two shocks:

$$g_{it} = \delta_t + \varepsilon_{it}. \tag{2}$$

The shock δ_t is common to all banks, e.g., a macroeconomic crisis that reduces the aggregate demand for credit. Instead, the shock ε_{it} is specific to a single bank, e.g., management's ability to run the bank. The common shock is computed as the average growth rate of loans of all banks in year t and the bank-specific shock is computed as the deviation of g_{it} from δ_t. This approach is adopted by Gabaix (2011) and di Giovanni et al. (2014).

As in di Giovanni et al. (2014), we work with the following decomposition of the aggregate growth:

$$\begin{aligned} g_{\mathcal{A}t|\tau} &= \mathcal{C}_{t|\tau} + \mathcal{E}_{t|\tau} \\ \mathcal{C}_{t|\tau} &= \sum_i w_{i\tau-1}\delta_t,\ \ \mathcal{E}_{t|\tau} \sum_i w_{i\tau-1}\varepsilon_{it}. \end{aligned} \tag{3}$$

For a given time period τ, weights $w_{i\tau-1}$ are fixed at their $\tau - 1$ values and combined with shocks from period t. The term $\mathcal{E}_{t|\tau}$ is the credit version of the *banking granular residual*, constructed by Buch and Neugebauer (2011) and Bremus et al. (2018) to study the impact of bank-specific shocks on aggregate outcomes. From Eq. (3), the aggregate variance $\sigma^2_{\mathcal{A}\tau}$ can be written as

$$\sigma^2_{\mathcal{A}\tau} = \sigma^2_{\mathcal{C}\tau} + \sigma^2_{\mathcal{E}\tau} + \mathrm{cov}_\tau, \tag{4}$$

where $\sigma^2_{\mathcal{C}\tau} = \mathrm{Var}(\mathcal{C}_{t|\tau})$ is the common volatility, $\sigma^2_{\mathcal{E}\tau} = \mathrm{Var}(\mathcal{E}_{t|\tau})$ is the bank-specific volatility and $\mathrm{cov}_\tau = \mathrm{Cov}(\mathcal{C}_{t|\tau}, \mathcal{E}_{t|\tau})$ is the co-variance between the shocks from different levels of aggregation. The estimator for $\sigma^2_{A\tau}$, $\sigma^2_{\mathcal{E}\tau}$ and $\sigma^2_{\mathcal{C}\tau}$ are, respectively, the sample variances of the $T = 65$ realizations of $g_{At|\tau}$, $\mathcal{E}_{t|\tau}$ and $\mathcal{C}_{t|\tau}$.

Following di Giovanni et al. (2014), we quantify the fraction of aggregate volatility that could be rationalized by bank-specific credit shocks alone by using the *relative standard deviation*

$$\mathcal{R}_\tau = \frac{\sigma_{\mathcal{E}\tau}}{\sigma_{\mathcal{A}\tau}}. \tag{5}$$

To grasp the intuition that motivates this paper, let us assume that shocks are uncorrelated across banks (i.e., $\mathrm{Cov}\left(\varepsilon_{it}, \varepsilon_{jt}\right) = 0,\ \forall i \neq j$) and the variance of shocks is identical across banks (i.e., $\mathrm{Var}\left(\varepsilon_{it}\right) = \sigma^2\ \forall i$). Under these assumptions, the aggregate bank-specific volatility is

$$\sigma_{\mathcal{E}\tau} = \sigma\sqrt{h_{\tau-1}},$$

where $h_{\tau-1}$ denotes the Herfindahl index (i.e., $h_{\tau-1} = \sum_i w^2_{i\tau-1}$). Therefore, we expect that the increase in concentration presented in Fig. 1 translates into a larger contribution of bank-specific shocks to aggregate volatility.

4. Results

Panel (a) in Fig. 2 shows that aggregate credit volatility is mainly driven by the bank-specific volatility. On average, the relative standard deviation $\mathcal{R}_\tau$ is 84%.[6] Panel (a) also depicts an increase in $\mathcal{R}_\tau$ after the restructuring process of the Spanish banking sector, which is in line with the intuition provided in Section 3. However, despite the fact that the dynamics of $\mathcal{R}_\tau$ closely resemble that of the Herfindahl concentration index h_τ (see Fig. 1), $\mathcal{R}_\tau$ does not fully provide an account for the extent to which the raise in concentration translates into a larger contribution of bank-specific shocks. To better understand the role played

[3] We use a broad measure of loans, including consumer, real estate and investment loans. Our dataset contains an average of 90% of the total number of credit institutions reported by the ECB.

[4] It affects 5% of observations, which are mainly small foreign branches.

[5] We keep those firms in SABI whose SIC code is between 2000 and 3999 and Global Ultimate Owner country (GUO country) is Spain.

[6] As a robustness check, we also perform the *exact* decomposition of the aggregate variance: $\sigma^2_{\mathcal{A}} = \sigma^2_{\mathcal{C}} + \sigma^2_{\mathcal{E}} + \mathrm{cov}$, where $\sigma^2_{\mathcal{C}} = \mathrm{Var}\left(\sum_i w_{it-1}\delta_t\right)$, $\sigma^2_{\mathcal{E}} = \mathrm{Var}\left(\sum_i w_{it-1}\varepsilon_{it}\right)$ and $\mathrm{cov} = \mathrm{Cov}\left(\sum_i w_{it-1}\delta_t, \sum_i w_{it-1}\varepsilon_{it}\right)$. The time averages of $\sigma^2_{\mathcal{A}\tau}$, $\sigma^2_{\mathcal{C}\tau}$ and $\sigma^2_{\mathcal{E}\tau}$ match those estimated using the exact decomposition. The time average of the relative standard deviation (5) is somewhat larger than that estimated using the exact decomposition (75%).

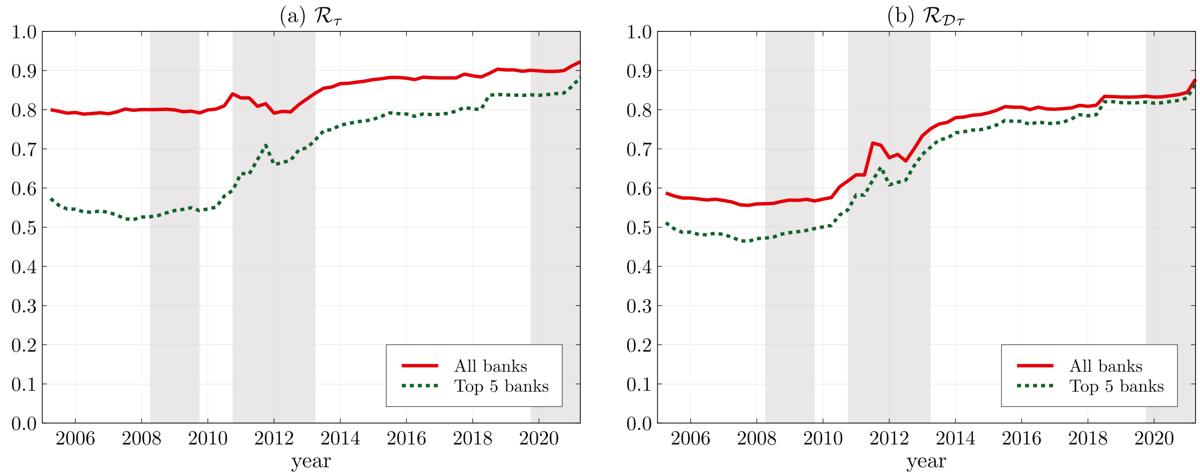

Fig. 2. Contribution of bank-specific credit shocks to aggregate credit volatility.

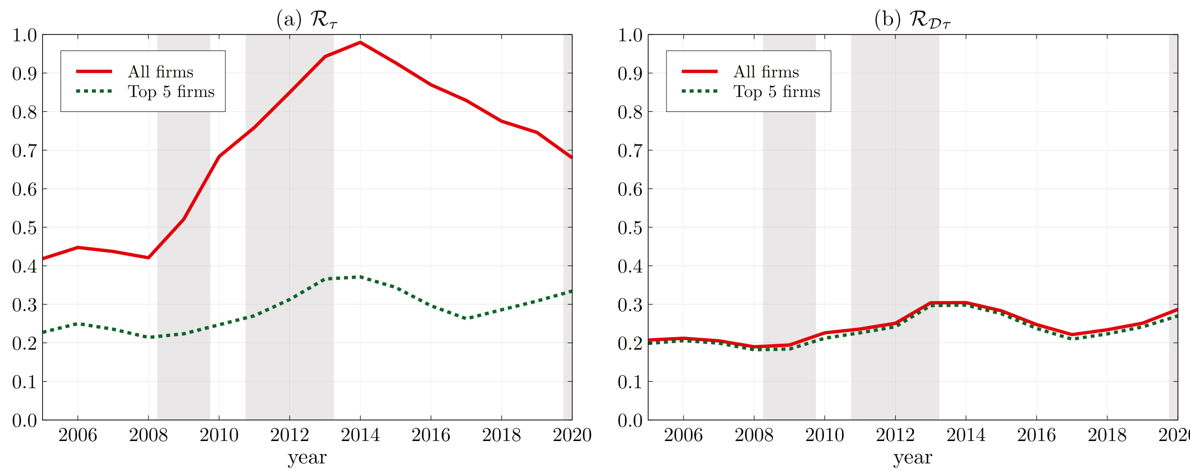

Fig. 3. Contribution of firm-specific sales shocks to aggregate sales volatility.

by h_τ in shaping $\mathcal{R}_\tau$, we follow (Carvalho and Gabaix, 2013) and decompose the aggregate bank-specific volatility $\sigma^2_{\mathcal{E}\tau}$ as follows

$$\begin{aligned}\sigma^2_{\mathcal{E}\tau} &= \mathcal{D}_\tau + \mathcal{L}_\tau \\ \mathcal{D}_\tau &= \sum_i w^2_{i\tau-1}\text{Var}\left(\varepsilon_{it}\right), \\ \mathcal{L}_\tau &= \sum_{i\neq j}\sum_i w_{i\tau-1}w_{j\tau-1}\text{Cov}\left(\varepsilon_{it},\varepsilon_{jt}\right).\end{aligned} \tag{6}$$

The diagonal term $\mathcal{D}_\tau$ captures the direct effect of shocks to banks on aggregate volatility and the non-diagonal term $\mathcal{L}_\tau$ captures the comovement between banks. The term $\mathcal{D}_\tau$ is Gabaix (2011)'s *granular volatility* and Carvalho and Gabaix (2013)'s *fundamental volatility*. Eq. (6) not only emphasizes the role of concentration in shaping aggregate fluctuations, but also the role of bank linkages as a potential amplification mechanism (Acemoglu et al., 2012). We quantify the contribution of the direct effect on aggregate volatility using the relative standard deviation

$$\mathcal{R}_{\mathcal{D}\tau} = \frac{\sqrt{\mathcal{D}_\tau}}{\sigma_{\mathcal{A}\tau}}. \tag{7}$$

Panel (b) in Fig. 2 shows that the direct effect of bank-specific shocks accounts for the overwhelming majority of the variation in aggregate volatility and therefore that the increase observed in $\mathcal{R}_\tau$ is primarily caused by the raise in D_τ. The dynamics of $\mathcal{R}_{\mathcal{D}\tau}$ and the intuition in Section 3 lead us to conclude that D_τ is commanded by the Herfindahl index h_τ. The correlation between h_τ and $\mathcal{R}_{\mathcal{D}\tau}$ is 97%. The increase in concentration has caused that the bank-specific shocks to the top 5 banks accounted for 87.8% of credit volatility in 2021:II. Hence, our results suggest that the Spanish banking sector is granular.[7]

di Giovanni et al. (2014) find that $\mathcal{L}_\tau$ is considerably more important than $\mathcal{D}_\tau$ to rationalize the aggregate sales volatility of the French manufacturing firms. Thus, we now check whether this is the case for the Spanish manufacturing sector. Panel (a) in Fig. 3 shows that the firm-specific component contributes substantially to aggregate sales volatility in the manufacturing Spanish sector and that this contribution experienced a rapid increase during the financial crisis. However, Panel (b) in Fig. 3 shows that the direct effect of firm-specific shocks only accounts for 25% of aggregate volatility. Therefore, in line with the evidence previously reported for France, firm linkages are also the main drivers of aggregate sales volatility in the Spanish manufacturing sector.

5. Concluding remarks

Taken together, our results indicate that the contribution of bank-specific credit shocks to aggregate credit fluctuations has

[7] Additionally, we find that the upper tail of the distribution of bank size is well characterized by a power distribution, as in Bremus et al. (2018).

increased dramatically since the restructuring process began. The rise has been mainly driven by the direct effect of bank-specific shocks, which, in turn, heavily depends on the degree of concentration. This is contrast to the widely studied manufacturing sector, in which firms linkages are the responsible for the amplification of firm-specific shocks. The explanation for this difference may lie in underlying network structure that characterizes each sector. Whereas the manufacturing sector is populated by a large number of heterogeneously interconnected firms that can propagate shocks across the sector and generate sizeable cascade effects (Acemoglu et al., 2012), the banking sector consists in a much smaller number of banks, thus restricting the potential cascade effects. In fact, we observe that the contribution of firm-specific shocks resembles to direct effect when restricting the sample to the top 5 firms, implying that the network almost disappears for small number of firms (see Fig. 3). Future research can shed some light on those aspects.

In the aftermath of the financial crisis, multiple countries experienced a significant increase in banking concentration (BIS, 2018). Hence, the present analysis can be extended to other countries to better understand the role played by bank-specific shocks in shaping aggregate fluctuations.

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