The Effect of the Global Financial Crisis on Market Structure in the Banking Sector: A Structural Analysis of the Data

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ABSTRACT: In this paper we present evidence of a simultaneous decrease in aggregate concentration and divergence in interest margins between large and small banks following the 2007-2008 global financial crisis. We offer two potential explanations for this seemingly contradictory outcome and assess their implications for interest rates and the supply of credit after the crisis using a structural model of Bertrand competition among banks of heterogeneous size.

Keywords: Heterogeneous banks, global financial crisis, concentration, market power, financial crisis response.

JEL Codes: F10, F32, F40, G33.

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1. Introduction

The purpose of this paper is to document and interpret key changes in the market structure of the banking sector during the global financial crisis across a panel of countries. Numerous figures in academia, policy, and the media have noted that one outcome of the recent global financial crisis has been an increase in the size of large banks, which appears in aggregate statistics as an increase in measures of concentration within the banking sector. We use a structural model to interpret data from bank balance sheets in a large panel of countries, finding that while many countries exhibit an increase in concentration as part of the fallout from the financial crisis, it varies across countries whether this change is associated with rising or falling market power.

Determining whether market power has increased is more complicated than it would appear at first glance. It is common practice for analysts to take an increase in concentration or in markups to by synonymous with an increase in market power\(^1\) However, in the case of banking, a number of studies\(^2\) show that measures of concentration often diverge from profit-based measures of market power. The issue is complicated by the fact that the most widely available measure of bank profitability—net interest margins (NIMs), the difference between interest revenues and interest payments—entangles both bank costs and the markup it charges borrowers over the bank’s own cost of funds.

Figure 1 provides an illustration of this phenomenon in the banking sector across a panel of countries before versus after 2008. We note several patterns. First, in many OECD countries, net interest margins rose for the largest 3 banks, but fell across the population of banks as a whole. This indicates an increase in market power among the largest 3 banks, a drop in market power for the average bank. In almost all OECD countries, the level of concentration for the largest 3 banks, measured as a herfindahl index of loan market shares, moved in the same direction for the three-bank measure as for the population as a whole— but in some countries the herfindahl indexes fell together,

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\(^1\)See US Department of Justice (2010) and European Commission (2014).

\(^2\)See, for example, Fernández and Perez (2005).
Table 1: Average change in net interest margins and concentration between the pre- and the post-crisis period

<table>
<thead>
<tr>
<th></th>
<th>ΔNIM</th>
<th>ΔHHI</th>
<th>ΔNIM3</th>
<th>ΔBC3</th>
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<td>OECD countries</td>
<td>-0.26</td>
<td>-0.71</td>
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<td>-1.55</td>
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<td>Euro area countries</td>
<td>-0.22</td>
<td>0.06</td>
<td>0.35</td>
<td>-0.67</td>
</tr>
<tr>
<td>Non-OECD countries</td>
<td>-0.14</td>
<td>-1.28</td>
<td>0.15</td>
<td>-3.05</td>
</tr>
</tbody>
</table>

while in others they rose. On average, the herfindahl measures of concentration fell (See Table 1). Yet the average hides a noticeable split in movements in banking sector concentration.

The relationship between NIMS and concentration is also nuanced. In the OECD, both measures of concentration increased for the U.S., Germany, France, the Netherlands,
and Italy. However, NIMs rose in the U.S. and the Netherlands, but fell in Germany, France, and Italy. The point is that, even when concentration measures move in the same direction for the 3-bank versus the all-bank herfindahl index, profit margins for the average bank do not move in the same direction as for the largest few banks. This makes it even more noticeable that in every country where concentration increased, NIMs increased for the largest 3 banks. We take from these observations that while an increase in concentration may not mean an increase in profit margins for the industry on average, it does suggest an increase in profit margins for the very largest banks. Bank heterogeneity is therefore important in any analysis of aggregate statistics.

While a number of studies also characterize the types of banking sector intervention across countries, there is no measure of the stance of policy toward large relative to small banks. Figure 2 helps make the point that policy likely was not neutral with respect to bank size. In OECD countries, one can see in the top left graph that authorities tended to reduce bank funding costs where banks were experiencing the most stress, in terms of reduced profit margins. However, in the top right graph, one can also see that NIMs were most likely to rise for the top 3 banks in countries where funding costs fell most. Comparing the top left and right graph, we see that the average bank did not fare as well as the top 3 banks for a given drop in funding costs. Where decreased funding costs are associated with rising NIMs for the largest banks but not for the average bank, we interpret this as indicating policy favored large banks. When concentration increases at the same time, we surmise that either (1) policy heavily favored large banks or (2) borrowers began searching harder for the banks with the lowest funding costs, increasing market share for the most efficiently operated lenders.

We introduce a structural model to disentangle concentration, costs, and the markup. In our model, policy affecting the distribution of lenders of a particular size in the banking sector affects the average markup. Disruption in lending relationships due to increased search for the cheapest loans by cash-strapped borrowers will also increase concentration but not bank profit margins. Our aim is twofold: (1) to devise a measure
Figure 2: Changes in funding costs and net interest margings between the pre- and post-crisis period

of where policy favors survival or expansion of large versus small banks, and (2) to draw conclusions regarding whether changes in market structure following the financial crisis may affect the cost and availability of credit in the future.

2. The Model

The economy is composed of a continuum of households and firms and a large but finite number of banks. Banks act as financial intermediaries by channeling funds from depositors (households) to borrowers (firms). In what follows, we present and describe the problem faced by each agent and their interactions.
2.1 Consumers

There is a continuum of infinitely-lived consumers in the economy in the interval \([0,1]\). Consumers derive utility from a composite of consumption goods, and disutility from working at the firms. The utility of a representative consumer is given by

\[
U(Q_t, H_t) = \ln(Q_t) - \frac{\psi}{1+\psi} H_t^{1+\psi}
\]

where \(Q_t\) denotes the composite homogeneous good, \(H_t\) is labor supplied at the firm; the parameter \(\psi\) is a scale parameter and \(\psi \geq 0\) is the inverse of the elasticity of labor supply with respect to wages.

Consumers maximize utility over time subject to the budget constraint:

\[
\max_{Q_t, H_t, D_{t+1}} \sum_{t=0}^{\infty} \beta^t \left( \ln(Q_t) - \frac{\psi}{1+\psi} H_t^{1+\psi} \right),
\]

with \(\beta \in (0,1)\) the discount rate, subject to:

\[
P_t Q_t + P_t D_{t+1} \leq W_t H_t + R^d_t P_t D_t.
\]

The left-hand side of the budget constraint denotes time \(t\) expenditures, where \(P_t\) is the aggregate price level on consumption goods and \(D_{t+1}\) are deposits at the bank. The right-hand side collects revenues by the consumer: labor income, with \(W_t\) being the nominal wage; and \(R^d_t P_t D_t\) denotes principal plus interest on the deposits at the bank made at time \(t\) at the gross interest rate \(R^d_t\). Households deposit wealth at any of the banks in the economy and receive their returns with certainty.

The first-order conditions from the consumer’s maximization problem are:

\[
\begin{align*}
[Q_t] & \quad \beta^t \frac{1}{Q_t} - \beta^t \lambda_t P_t = 0, \\
[H_t] & \quad -\psi H_t^{\psi} \beta^t + \lambda_t \beta^t W_t = 0, \\
[D_{t+1}] & \quad -\beta^t \lambda_t P_t + \beta^{t+1} \lambda_{t+1} P_{t+1} R^d_{t+1} = 0, \\
[\lambda_t] & \quad W_t H_t + R^d_t P_t D_t - P_t Q_t + P_t D_{t+1} = 0.
\end{align*}
\]
These first-order conditions can be simplified to

\[
\Psi H_t^\psi Q_t = \frac{W_t}{P_t}, \quad (1)
\]

\[
\frac{1}{Q_t} = \beta \frac{1}{Q_{t+1}} R_t^d, \quad (2)
\]

\[
W_t H_t + R_t^d P_t D_t = P_t Q_t + P_t D_{t+1} \quad (3)
\]

where equation (2) is the intratemporal labor-leisure choice; equation (3) is the intertemporal Euler equation; and equation (3) is the consumer’s budget constraint.

In what follows, we abstract from labor market frictions, assuming that labor markets are perfectly competitive. Notice that equation (3) implies a steady-state gross nominal interest rate on deposits equal to

\[
\bar{R}_d = \frac{1}{\beta}.
\]

We use the intertemporal problem to derive this interest rate and from this point focus on the steady state, omitting time subscripts.\(^3\)

### 2.2 Firms

There is a continuum of firms of mass one in charge of the production of intermediate goods \(Y(i)\). These intermediate goods are then aggregated by consumers to generate their composite good, \(Q\)

\[
Q = \left( \int_0^1 Y(i) \frac{\sigma - 1}{\sigma} di \right)^{\frac{\sigma}{\sigma - 1}},
\]

where \(\sigma > 1\) determines the elasticity of substitution between the various inputs. Consumers solve the following maximization problem that determines the demand of individual input goods \(Y(i), i \in [0,1]\):

\[
\max_{\{Y(i)\}_{i \in [0,1]}} PQ - \int_0^1 P(i) Y(i) di,
\]

subject to 2.2, where \(P(i)\) denotes the price of the intermediate good \(i\). This yields input demand functions of the form

\[
Y(i) = \left( \frac{P(i)}{P} \right)^{-\sigma} Q, \quad (4)
\]

\(^3\)For a small open economy, this interest rate on deposits can be replaced by the world interest rate on interbank loans or other sources of bank funding.
where $P(i)$ is the price that the firm charges for its good, $P$ is the aggregate price index,

$$P = \left( \int_0^1 P(i)^{1-\sigma} \, di \right)^{\frac{1}{1-\sigma}}$$

and $Q$ is aggregate consumption.

Firms employ a constant returns to scale technology with labor, $H(i)$, as the only production input, and a country-wide efficiency parameter $A$: $Y(i) = AH(i)$. We assume there is working capital, that is, firms need to hire workers before production takes place. The funding for production is due before firms receive revenue from sales, so they must borrow the working capital from financial intermediaries in order to produce. To do this, they apply for loans from different banks and negotiate the best offer possible. The applications require a fee $v$, as in de Blas and Russ (2012), so each firm applies to only a subset $N(i)$ from the country’s total population of banks $J$ and takes the lowest interest rate quote that it can get from any bank in that group. Thus, the interest rate the firm pays ($R(i)$) will depend on which bank it ultimately finds and chooses. We also assume that the number of applications is the same for all firms, so $N(i) = N$ for all $i$. The firm’s maximization problem is therefore

$$\max_N \left\{ \int_{R^l}^{\infty} \max_{P(i)} [P(i)AH(i) - R(i)WH(i)] \, dF_{1:N}(R(i)) - Nv \right\},$$

subject to 4 where $F_{1:N}(R(i))$ is the probability that a firm $i$ can negotiate an nominal gross interest rate less than or equal to some level $R(i)$ given that it submits $N$ different applications for a loan. Below, we will assume that intermediate goods producers take the nominal wage as given.

The first-order conditions from the firms’ problem are

$$[P(i)] \quad Y(i) + P(i)(-\sigma) \left( \frac{P(i)}{P} \right)^{-\sigma - 1} \frac{Q}{P} - R(i) \frac{W}{A} (-\sigma) \left( \frac{P(i)}{P} \right)^{-\sigma - 1} \frac{Q}{P} = 0 \quad (5)$$

$$[N] \quad \frac{WQ}{A} \frac{\sigma}{\sigma - 1} \int_R^{\infty} \left[ (1 - \sigma) \left( \frac{R(i)}{R} \right)^{-\sigma} \frac{\partial R(i)}{\partial N} \right] \, dF_{1:N} R(i) = v. \quad (6)$$

The first yields a pricing rule,

$$P(i) = \frac{\sigma}{\sigma - 1} \frac{WR(i)}{A} \quad (7)$$

2.3 Market structure in the banking sector

There is a finite number of banks \( J \) in the economy serving a countably infinite number of borrowers within the interval \([0,1]\), similar to the Salop model in Andrés, Arce, and Thomas (2013) (hereafter, AAT). Banks receive deposits \( D \) from households every period, paying depositors the \( \overline{R}^d \) gross interest rate. As in AAT, we abstract from modelling the deposit market to focus on the lending activities of banks, assuming perfect competition in the market for deposits.

Banks incur a monitoring cost when lending to firms. Banks vary according to how great this cost is. Each bank’s efficiency in this respect is captured by an efficiency parameter \( Z \). The number of banks in a particular country with an efficiency parameter no less than \( z^\theta \) is governed by a Poisson distribution with a rate parameter \( T \).\(^4\) The efficiency parameter can represent either the bank’s ability to screen borrowers at the beginning of each period or its ability to recover loans in default through monitoring. Either way, expected losses per unit of loans due to assets remaining unrecovered after default is given by \( \frac{\gamma \mu}{Z} \), with \( \gamma \mu \) being the expected loss due to default in the absence of screening or monitoring. Given this technology, the relationship between the level of performing (successfully repaid) loans and the level of deposits for some bank \( j \) is

\[
L(j) = \frac{C(j)}{\overline{R}^d} D(j),
\]

where the unit cost parameter \( C(j) \) is given by

\[
C(j) = \overline{R}^d \left( 1 + \frac{\gamma \mu}{Z(j)} \right).
\]

This specification implies that the bank pays interest on deposits used for both performing and (ex post) non-performing loans, where \( \gamma \) is the fraction of bank \( j \)'s loans that are non-performing and \( \mu \) is the monitoring cost or fraction of principal lost. For simplicity, we assume that the default probability is the same for all firms in any period, though we can equivalently interpret efficiency as skill in screening that could help the bank predict

\(^4\)A country with a high intermediation technology parameter \( T \) and a high shape parameter \( \theta \) will have more efficient banks on average than low-\( T \) countries, and banks that are more similar in size than a low-\( \theta \) country.
whether a firm will default in a particular period with an accuracy of \(1 - \frac{1}{z}\), or monitoring could help the firm recover a fraction \(1 - \frac{1}{z}\) of assets in default.

Note that low-efficiency (high-cost) banks must raise more deposits to supply each unit of lending. The number of banks with cost per unit of loans net of the deposit rate less than or equal to some level \(c = (\bar{\epsilon} - R^d)\theta\) is then governed by a Poisson distribution with the rate parameter \(\lambda = T(R^d\gamma\mu)^{-\theta}\), similar to the model of heterogeneous firms by Eaton, Kortum, and Sotelo (2012), but with a shift parameter \(\bar{R}^d\).

In an economy with many banks, firms cannot possibly apply to every bank for a loan in search of the lowest rate. Instead, each firm applies to \(N < J\) banks. We assume that firms choose these banks at random, so that the probability any particular bank receives an application from firm \(i\) is equal to \(\frac{N}{J}\).\(^5\) The firm reports the preliminary interest rate quotes it gets in response to each accepted application to each bank in this pool and negotiates the lowest possible rate—Bertrand competition with loans from each bank being perfect substitutes. The number of banks that a particular firm will encounter (on average) with unit cost less than or equal to some level \(c\) is lessened by the need to search.

The search friction is reflected in a lower Poisson rate parameter, which becomes \(\frac{N\lambda}{J}\).\(^6\) Then the probability that the most efficient bank it applies to has a unit cost less than or equal to some value \(c_1\) is given by

\[
f_{C_1(i)}(c_1) = \left(\frac{N\lambda}{J}\right) \theta c_1^{\theta-1} e^{-\frac{N\lambda}{J}c_1}, \tag{10}\]

where \(c_1\) is the cost of the best found bank, net of the deposit rate. We assume that the shape parameter \(\theta\) is greater than \(1 - \sigma\) to assure the existence of the \((1 - \sigma)^{th}\) moment. On average, a firm can find a more efficient bank if it sends out more applications: the wider the search \(N\),\(^7\) the lower will be the expected cost of the best bank to which a firm applies. The firm decides the optimal number of banks it will apply to knowing that

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\(^5\)This assumption can be relaxed to allow firms to 'find' more efficient banks with greater frequency than less efficient banks. We use the uniform probability here for simplicity.

\(^6\)The probability that firm \(i\) applies to a particular bank \(j\) is \(\frac{N}{J}\), so the search produces a phenomenon called “thinning” or “splitting”, producing a second Poisson process governing the number of banks firm \(i\) finds.

\(^7\)Note that \(N\) must be at least one for any active firm to receive a loan and manufacture output.
applying to more banks will reduce its expected interest rate, subject to a fee $v > 0$ for each application. Because we assume that all firms apply to the same number of banks, the distribution is the same for any firm $i$ and thus needs no indexing by firm.

The search friction helps pin down the fraction of firms that each bank will serve. The most efficient bank in the entire sector will be able to underprice all rival banks for any client that applies. It serves all customers that apply to it, the fraction $\frac{N}{J}$. The least efficient $N - 1$ banks in the sector will not be able to successfully compete for any customer that applies, so their market share is zero– they exist as a competitive threat, but are inactive, making no loans and taking no deposits (or transferring any deposits they receive costlessly through a perfectly competitive interbank market). To compute the fraction of firms served by banks between these extremes, it is useful to rank banks from 1 to $J$, with rank $j = 1$ being the lowest-cost lender and $j = J$ representing the highest. Then the probability that a bank $j$ gets a customer is the probability that the bank gets an application from the customer times the probability that the customer does not also apply to a more efficient bank. This fraction $\alpha$ for any bank $j$ depends on bank $j$’s rank and is given by

$$\alpha_j = \frac{N}{J} \left(1 - \frac{N}{J}\right)^{j-1} \quad (11)$$

The object of our quantitative analysis is to use our structural model of bank lending and interest rate spreads to estimate the level of search, $N$, and the level of expected losses $\gamma \mu$ before and after the crisis for a panel of countries. To this end, we use this distribution of lending costs in the next section to derive a distribution for interest rate spreads and bank lending in the next section.

### 2.4 Strategic pricing of loans

At this point, the strategic behavior of banks becomes important. The interest rate that a firm ultimately pays depends not only on the costs of the best bank it successfully applies to, but also the cost of the second-best bank. As the firm negotiates to get the best rate, the best bank in a firm’s search pool can not charge an interest rate higher than
the marginal cost of its next best rival for the firm’s business. Otherwise, the next best rival will lure the client away with a lower interest rate. With the Poisson distribution described above, the distribution of bank costs is Generalized Gamma, with the shape parameter varying by the rank of bank cost in the pool of \( N \) loan applications.\(^8\)

The bank cannot charge a price greater than the lending cost of its next best rival for its customer \( i \), \( C_2(i) \). Because of our use of the Poisson distribution, the distribution of markups across an individual bank’s borrowers is independent of its lending cost—all banks have the same average markup. We can see this by noting that the markup a winning bank charges over its own lending cost \( i \) in our Bertrand framework is given by

\[
M(i) = \frac{C_2(i)}{C_1(i)}
\]

(12)

The distribution of the constrained markup—the markup that emerges if the bank’s loan pricing is bounded by its next best rival for firm \( i \)’s business, is the distribution of the ratio of two generalized gamma variables. In Appendix B we derive the distribution and show that it reduces to Pareto with shape parameter \( \theta \) —a result here closely related to that in Bernard, Eaton, Jensen, and Kortum (2003). It is identical across firms \textit{and} for all banks regardless of cost,\(^9\)

\[
F_M(m) = 1 - m^{-(\theta)}.
\]

(13)

The average markup is then given by \( E[M(j)] = \frac{\theta}{\theta - 1} \). Note that any policy that changes the shape of the distribution, expressed by a change in the dispersion parameter \( \theta \), will affect the profit margins of banks and the cost of credit for their customers.

In summary, the average markup that a bank will charge across all of its customers is identical for all banks and those with lower costs will charge lower interest rates on average. Below, we show how this results in more efficient banks attaining a larger market share.

\(^8\)The lowest cost parameter \( C_1(i)^\theta \) is distributed Erlang(1, \( \frac{N\lambda}{1} \)) or exponential, the second-lowest cost raised to the same power is distributed Erlang(2, \( \frac{N\lambda}{2} \)), the third is Erlang(3, \( \frac{N\lambda}{3} \)), and so on.

\(^9\)This invariance by rank is due to the Poisson assumption, as explained in de Blas and Russ (2015). See Herrenbrueck (2013) for other applications within a binomial family of distributions.
2.5 Credit market clearing and the market share of banks

For the credit market to clear, first the amount of loans demanded by each firm $i$ must equal the amount necessary to satisfy demand for its good,

$$L^D(i) = \frac{W}{A}H(i) = \frac{W}{A} \left( \frac{P(i)}{P} \right)^{-\sigma}. \quad (14)$$

The pricing rule in equation (7) implies an aggregate price level $P$ equal to

$$P = \frac{\sigma}{\sigma - 1} \left( \frac{W}{A} \right) \left[ \int_0^1 R(i)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}. \quad (15)$$

Let $R$ be the aggregate interest rate,

$$R^{1-\sigma} = \left[ \int_0^1 R(i)^{1-\sigma} di \right]. \quad (16)$$

Then, $R^{1-\sigma}$ is the $(1 - \sigma)^{th}$ moment of the winning interest rate for any firm $i$, $E[R(i)^{1-\sigma}] = E[C_2(i)^{1-\sigma}]$. Note that the cost of the next-best rival to the winning bank $j$, $C_2(i)$, is not governed by special characteristics of customers that vary across $i$ and is distributed $\Gamma \left( 2\theta, \frac{N\lambda}{J} \right)$.\(^{10}\) Thus, we can write\(^{11}\)

$$R^{1-\sigma} = E[C_2(i)^{1-\sigma}] = \lambda \frac{\sigma - 2\theta}{\sigma - 2} \Gamma \left( 4 - \frac{\theta}{\sigma} \right). \quad (17)$$

To assure that this moment exists, we further assume that $4\theta > \sigma$. In economic terms, this means that the distribution of bank can’t be too disperse (in this case, too fat-tailed) relative to consumers’ love of variety. Otherwise, firms borrowing from any bank other than the lowest-cost bank in existence would go out of business as consumers substitute away from their more costly goods financed with costly credit.

The aggregate price level is a function of this revenue-weighted average interest rate. The distribution for the lending cost of some lowest-cost bank among $N$ applications, $C_1(i)$, is given by equation (10), which is Gamma \(\theta, \frac{N\lambda}{J} (R^\mu)^{-\theta} \).\(^{10}\) $C_2(i)$ is distributed

$$f_{C_2(i)}(c_2) = \left( \frac{N\lambda}{J} \right)^2 \theta c_2^{2\theta-1} e^{-\left( \frac{N\lambda}{J} \right)c_2}. \quad (13)$$

\(^{10}\)See Mood, Graybill, and Boes (1974), page 541, for computation of moments of a Gamma distribution.
To compute the market share of a particular bank with the \( j \)th highest cost in the banking sector, we must compute the interest rate that the bank charges each customer, then take the average over all customers, weighted by the size of each loan. So, we need to compute the expected cost of the next-best rival for some firm \( i \)'s loan, given that bank \( j \) is the winning bank for firm \( i \). Note that this distribution is conditional on bank \( j \)'s lending cost and thus varies across banks, but it does not vary \emph{ex ante} across firms applying to bank \( j \). Thus, we can refer to the cost of the next-best rival for bank \( j \)'s borrower using the bank’s rank, \( C_2(j) \). The distribution of \( C_2(j) \) is derived in the Appendix. The distribution yields an expression for the \( (1 - \sigma) \)th moment conditional on \( C(j) \) taking a particular value \( c_j \),

\[
E[R(j)^{1-\sigma}] = E[C_2(j)^{1-\sigma}] = \frac{c_1^{1+2\theta-\sigma} \exp\left(\frac{-1-\theta+\sigma}{\theta} c_1^\theta \lambda\right)}{1+c_1^\theta \lambda} \expint\left(-\frac{1-\theta+\sigma}{\theta}, c_1^\theta \lambda\right).
\]  

(18)

The market share of any bank with sectoral rank \( j \) then is determined by the ratio of it’s own interest rate averaged across customers, which we call \( R(j) \), to the aggregate interest rate \( R \):

\[
S(j) = \alpha_j \left(\frac{R(j)}{R}\right)^{1-\sigma}.
\]

(19)

### 3. Structural Estimation

We estimate the parameters of the Weibull distribution on banking costs for a sample of 21 countries from Bankscope.\footnote{The final number of banks employed in the estimation depends on the availability of data for the whole sample and the number of banks.} Table 2 provides summary statistics for our sample. We perform several estimation analyses, using data from 2005-2012, and also comparing the effects of the financial crisis by studying the estimates for the years 2005 and 2009.

We use the data from Bankscope to fit a Weibull distribution for costs to match the distribution of the ratio of deposits to loans observed separately for each country. The estimation method is maximum likelihood. To this end, we use a transformed version of
Table 2: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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<tbody>
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<td><strong>Full sample (2005-2012)</strong></td>
<td></td>
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</tr>
<tr>
<td>NIM (all banks)</td>
<td>53965</td>
<td>3.39</td>
<td>2.62</td>
<td>-2.21</td>
<td>26.67</td>
</tr>
<tr>
<td>NIM (three largest banks)</td>
<td>53965</td>
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<td>0.52</td>
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<td>Herfindahl index</td>
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<td>6.05</td>
<td>2.27</td>
<td>33.46</td>
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<tr>
<td>3-bank concentration ratio</td>
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<td>44.10</td>
<td>15.63</td>
<td>17.60</td>
<td>87.10</td>
</tr>
<tr>
<td>Total assets (in bn USD)</td>
<td>53965</td>
<td>20.40</td>
<td>141.68</td>
<td>0.00</td>
<td>3807.89</td>
</tr>
<tr>
<td><strong>Before 2008</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NIM (all banks)</td>
<td>20522</td>
<td>3.44</td>
<td>2.59</td>
<td>-2.18</td>
<td>26.61</td>
</tr>
<tr>
<td>NIM (three largest banks)</td>
<td>20522</td>
<td>2.10</td>
<td>1.89</td>
<td>0.52</td>
<td>10.77</td>
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<td>6.76</td>
<td>2.27</td>
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<td>20522</td>
<td>43.24</td>
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<td>16.65</td>
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<td>3807.89</td>
</tr>
<tr>
<td><strong>After 2008</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NIM (all banks)</td>
<td>26674</td>
<td>3.31</td>
<td>2.61</td>
<td>-2.21</td>
<td>26.56</td>
</tr>
<tr>
<td>NIM (three largest banks)</td>
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the Weibull distribution,
\[ G(c) = 1 - e^{\left(\frac{\tilde{c}}{\chi_1}\right)^{\chi_2}}, \]
which corresponds to \( T = \left(\frac{1}{\chi_1}\right)^{\chi_2} \frac{1}{J} \left(R^d\gamma\mu\right)^{-\theta} \), \( \theta = \chi_2 \), and \( \tilde{c} = c - R^d \) in equation (10) in the text. We use for \( R^d \) the net interest rate on expenses. Notice that we use the net interest rate instead of the gross in order not to restrict the lower bound in the estimation. We estimate \( \chi_1 \) and \( \chi_2 \) by maximum likelihood. The parameter \( \theta \) corresponds to the shape parameter in the Weibull function, which governs the dispersion of bank costs and thus bank size. Eaton and Kortum (2002) find estimates of \( \theta \) between 3.6 and 8.32. With endogenous markups, BEJK find \( \theta = 3.29 \). In our case, \( \hat{\theta} \) is the maximum likelihood estimator based on the distribution of costs (the ratio of deposits to loans) across all banks in each country. Our findings show values for \( \hat{\theta} \) between 1.76 and 8.76 in 2005, a range which encompasses values reported in these previous studies for manufacturing firms. We use the standard bootstrap method to obtain 95% confidence intervals.

Once we have \( \hat{\theta} \) and \( \hat{\chi_1} \), we estimate the number of applications per country and year, \( N \) use the (loan) market shares. We impose that the estimated \( N \) is larger than 1 and less than \( J \) to be consistent with the model. We estimate the number of applications using a large-scale algorithm.

Finally, in order to recover \( T \) we would need data on the fraction of non-performing loans (\( \gamma \)) and monitoring costs (\( \mu \)). Bankscope provides us with data for non-performing loans, but not for monitoring costs, so as a first approach, we are estimating the joint product \( \tilde{T} = T (\gamma\mu)^{-\theta} \).

4. Results

The results are provided in Table 3 and 4 for the period pre-crisis (2005) and post-crisis (2009). Confidence intervals at 95% are computed using bootstrapping over 1000 iterations.
Table 3: Estimates of the degree of search $N$ and the dispersion $\theta$, and average funding costs in 2005

<table>
<thead>
<tr>
<th>Countries</th>
<th>$\hat{N}$</th>
<th>$N_{low}$</th>
<th>$N_{up}$</th>
<th>$\hat{\theta}$</th>
<th>$\theta_{low}$</th>
<th>$\theta_{up}$</th>
<th>$R^d$</th>
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<td>4.46</td>
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Table 4: Estimates of the degree of search $N$ and the dispersion $\theta$, and average funding costs in 2009

<table>
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<tr>
<th>Countries</th>
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<th>$N_{up}$</th>
<th>$\hat{\theta}$</th>
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</table>

The preliminary estimates provide information about banking sectors which differ widely across countries. For most of the countries analyzed, concentration has decreased in 2009 compared to 2005 (an increase in $\theta$), with the exception of Switzerland, China, Great Britain, Japan, Mexico, Panama and the United States. In the case of the number of applications, these first estimations show a lot of heterogeneity within and across years. It is noticeable that for the case of Great Britain, Panama and the United States, the number of applications increases. As mentioned in the introduction, this increase may be due to disrupted lending relationships or an increase in search because of the crisis. This, together with the fall in $\theta$, can be interpreted as a clear increase in concentration in these countries. In particular, for the case of Great Britain and the United States it would be consistent with the increased NIMs of the three largest banks observed for OECD
countries reported in Table 1, but inconsistent with the decrease in the average NIMs. We can infer from this that some additional factors may have influenced larger banks versus small banks, for example non-neutral effects of policy. This is food for continued research.

Finally, regarding the preliminary estimations for $T$, our technology parameter not reported in the current version, offer an scenario with a decrease in technology in 2009 compared to 2005. However, more work needs to be done on this parameter, since it is $\hat{T} = T (\gamma \mu)^{-\theta}$, and thus it is capturing jointly the variations in technology, monitoring costs, and fraction of non-performing loans. We may infer that both $\gamma$ and $\mu$ have increased during the crisis driving $\hat{T}$ down. Future estimations will try to disentangle these effects.

5. Conclusions

We have identified divergence in the market power of the largest banks relative to other banks across a sample of countries during the global financial crisis, while changes in concentration in the banking sector varied widely across countries. We estimate a structural model to capture disruptions on the demand side of the market, through search, and changes in the distribution of bank size. Divergence in the market power of large versus small banks is attributed to de facto non-neutrality in policy response to crisis. In ongoing work, we will expand on this benchmark model and analysis to develop a new indicator of policy intervention that captures the degree to which policy is most amenable to large or smaller bank profit margins and lending growth.
References


