Market competition and strategic interaction in the Spanish FinTech industry

David Peón[ab], Manel Antelo[c], Yanfei Sun[d]

Abstract

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Keywords: FinTech, digital finance, Panzar-Rosse H statistic, Boone indicator, Lerner index, conjectural variation

JEL Classification: G23, G21, L10.

[a] Department of Business, University of A Coruna (UDC), and CISPAC. Campus Elviña s/n, 15071 A Coruña (Spain). (2) Ted Rogers School of Management (Toronto Metropolitan University). Dpt. Finance. 55 Dundas Street West. Toronto, ON, M5G 2C5 (Canada).

[b] Corresponding author. E-mail: *david.peon@udc.es*. ORCID 0000-0002-5212-4385

[c] Department of Economics, University of Santiago de Compostela. Santiago de Compostela (Spain) and ECOBAS.

[d] Ted Rogers School of Management (Toronto Metropolitan University). Dpt. Finance. Toronto (Canada).

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BLIND FOR REVIEW

Abstract

Financial technology (FinTech) is driving innovation in the financial industry worldwide. This article contributes to answer the question of whether FinTech firms and traditional financial institutions compete or collaborate. We use the decade of 2010s in Spain as a case study – a country with a world-leading banking sector before the global financial crisis and now third in Europe by number of FinTech firms. Competition is measured using the Herfindahl–Hirschman index, the Panzar-Rosse H statistic, the Lerner index, and the Boone indicator, while an oligopolistic conjectural variation model tests interaction between independent firms and bank-owned ventures. The results suggest sharp reductions in concentration measures and moderate, albeit increasing, market competition in the context of a twentyfold increase in revenues during the decade. Our conjectural model also shows the strategic interactions existing between banks and independent firms, with a clear pattern of competition rather than collaboration by the incumbent banks.

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1. Introduction

The last decade has witnessed the rise of FinTech as a global phenomenon. Information technology is driving innovation in the financial industry, both in terms of new ventures – with total investments of USD 226.5 billion in 2021, ten times more than in 2013 (KPMG, 2022) – and the digitalization of the financial industry. A relevant question is whether FinTech and traditional banks will compete or collaborate; that is, if we will observe a substitution effect and disruptive innovation or a complementary effect and collaborations (Li *et al.*, 2017; Zveryakov *et al.*, 2019). Evidence of the negative impact of FinTech on bank performance include Gomber *et al.* (2017) and Phan *et al.* (2020), which may have motivated banks' reaction to invest in FinTech start-ups in the form of joint partnerships, service outsourcing, venture capital funding, and acquisitions (PwC, 2016; Hornuf *et al.*, 2021), as well as launching their own FinTech projects (Lee and Shin, 2018).

The motivation of this article is to delve into this interaction. To such purpose, we use the FinTech industry in Spain as a case study, with a twofold goal: to assess the degree of market competition in the industry over the past decade, and to derive to which extent the strategic interaction among incumbent banks and independent FinTech firms explain competition. A reason to choose the Spanish industry is that all private firms must disclose their financial statements in accordance with the Spanish General Accounting Plan, which allows the study of market competition by considering firms of any size – something that would be unfeasible in countries such as US and Canada. A second reason is that the Spanish banking industry was one of the world leaders until the global financial crisis hit hard. Then came the rise of a FinTech industry in recent years. By 2020, Spain had 6% of the 3,500 FinTech in Europe – in third place by number of firms (Deloitte, 2020). In contrast, it ranked seventh by level of consumer adoption of FinTech (E&Y, 2021). Total investment amounted EUR 542 million in 2021, an increase of 151% compared to 2020, mainly through private equity and in firms oriented towards business-to-business services (Sánchez and Quintanero, 2022). In this context, the incumbent banks have made a significant investment effort, with a share in FinTech ventures valued at EUR 65 billion by end-2021.[1] However, most of this effort comes from BBVA and Santander's investments outside Spain, leaving the question open on whether banks are willing to compete or collaborate with local FinTech firms.

This research contributes with an analysis of competition by payment services providers and lending companies in the Spanish FinTech industry during the decade of 2010s. We estimate different indicators of market power to measure the degree of market competition, including the Herfindahl–Hirschman index (HHI), the Panzar-Rosse H statistic (Panzar and

[1] Expansión Dec.2021: www.expansion.com/empresas/banca/2021/12/02/61a7f6f2468aeb9d488b45fb.html

Rosse, 1987), the Lerner index (Lerner, 1934), and the Boone indicator (Boone, 2008). We then use an oligopolistic conjectural variation model (Spiller and Favaro, 1984) to test competition among the FinTech ventures of the incumbent banks and the independent FinTech firms. We obtain three main findings: (i) revenues in the industry increased twentyfold during the period, with higher growth rates and sharp reductions in concentration after 2014; (ii) the measures of market power show only moderate levels of competition among all firms in the industry, either with a peak in 2015 according to the H statistic or with an increasing trend afterwards according to the Boone indicator and Lerner index; (iii) instead, our conjectural model shows that strategic interactions exist between FinTech firms owned by banks and the independent FinTech, with a clear pattern of competition, rather than collaboration, by the FinTech owned by banks.

The structure of the article is as follows. Section 2 provides the conceptual framework, with a brief review of the literature of market competition and a closer look at the case study. In Section 3, the methodology and hypotheses to be tested are defined. The empirical analysis and the discussion of results are provided in two separate sections: Section 4 on indicators of market competition in the industry, and Section 5 on the analysis of strategic interaction among independent and bank-owned FinTech firms. Finally, Section 6 concludes.

2. Conceptual framework and case study

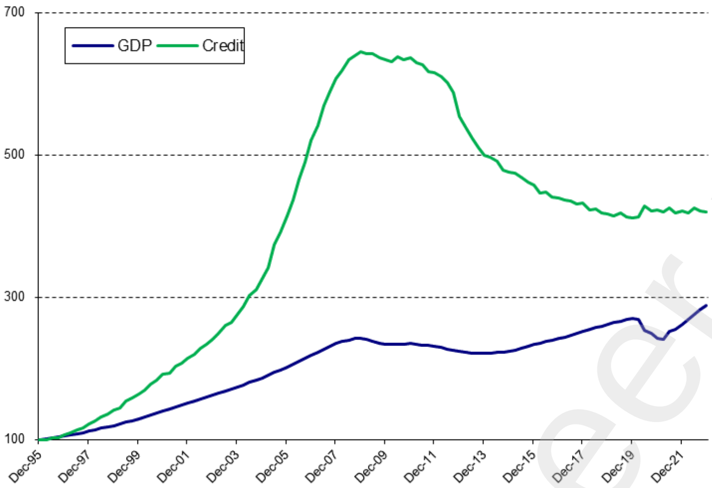
In this section, we first provide an approach to our case study – the rise of the FinTech industry in Spain in recent years – and then describe the conceptual framework of our research with a review of the literature on models and indicators of market competition.

2.1 The emergence of the FinTech industry in Spain

The global financial crisis hit the Spanish banking industry hard, which since the 1990s had been a world leader (Kase and Jacopin, 2008; Santos, 2017), with strong rates of market penetration and at the cutting edge in technology (Bátiz-Lazo et al., 2011; Maixé-Altés, 2016). The boom and bust of credit (see Figure 1) led to the complete restructuring of the banking industry after 2010, with the demise of most savings banks and the concentration of more than fifty banks into ten groups holding 80% of the assets (Peón and Guntín, 2021).

More recently, a new threat appeared, both at the national and international level: the rise of FinTech firms. Their disruptive innovation challenges the incumbent banks in most of the traditional services they provide, such as means of payment, credit, investment vehicles and advisory services, and with the provision of new services and entering areas underserved by traditional banks (Jagtiani and Lemieux, 2018). We mapped the industry in Spain during the 2010s,[2] with a hand-collected list of brands in five market niches (some firms operating in more than one): neobanks and payment services, credit (personal and corporate credit, comparators, crowdfunding-lending), investment services (trading, wealth management, personal and enterprise financial management), insurtech (insurance providers, including comparators), and other financial services (including cryptocurrencies and blockchain, know-your-customer and security-identity-fraud services, and other services).

Figure 1. Credit to households and firms in Spain, 1996-2022 (1996 base = 100).



Source: Banco de España (BdE), Instituto Nacional de Estadística (INE)

Our inventory is more complete than those by Spanish FinTech associations and existing academic taxonomies (e.g., Carbó-Valverde et al., 2020; Sánchez and Quintanero, 2022). Thus, we identify more than 600 brands, although many of them are inactive today. These brands are owned by about 480 companies, of which 395 have some financial information available in the Spanish commercial registry for the decade 2010-2019. While 309 of these firms were still active by the end of 2019, only 23 (102) had revenues above 10 million (1 million) euros. Table 1 shows the number of FinTech firms with positive annual revenue, and the sum of total revenues in the industry from 2010 to 2019. The boom is clear, with a fivefold increase in the number of companies by the end of the decade and a tenfold increase in total revenues. The largest increase is observed in payment services, particularly in terms of total revenues, followed by the credit niche. By 2019, the two niches combined accounted for more than 80% of industry revenues (1.28 billion out of 1.57 billion euros),[3] with the number of firms increasing sevenfold and total revenues more than twentyfold.

[2] Details of this compilation provided in Section 4.

[3] Since some firms operate in more than one niche, the sum of revenues in all five segments is somewhat higher than the industry total. Thus, the 1.28 billion revenues of payment services and credit niches represent 81,1% of the total (1.57 billion), but 72.2% of the 1.77 billion revenues if niche overlaps are considered (see Table 1).

Table 1. Number of active FinTech firms and total revenues by market niche, 2010-2019.

Number of FinTech by niche and year

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
payment	9	14	20	25	37	39	45	52	54	60
credit	12	19	24	33	48	62	76	87	93	92
investment	19	22	29	31	34	50	59	65	70	79
insurtech	11	13	14	16	18	21	19	25	32	33
financial servs	22	26	29	35	45	50	59	68	76	80
By ownership:										
incumbent	1	2	5	8	10	11	15	16	18	20
independent	63	81	100	117	152	185	216	251	273	289
TOTAL	**64**	**83**	**105**	**125**	**162**	**196**	**231**	**267**	**291**	**309**

Total revenues by niche and year (million EUR)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
payment	21.8	93.2	113.1	128.5	190.6	317.8	472.0	598.5	724.1	774.3
credit	28.7	29.7	45.9	66.5	84.2	125.5	197.8	273.1	377.3	501.7
investment	44.9	42.9	43.5	47.3	57.8	61.8	72.4	83.8	94.0	117.9
insurtech	53.0	48.8	56.4	62.0	72.6	78.1	77.0	82.7	131.2	124.8
financial servs	33.1	39.9	46.1	48.1	74.3	84.3	88.9	115.9	184.1	249.8
By ownership:										
incumbent	0.4	70.0	79.8	92.5	138.3	225.7	213.0	283.5	329.5	361.0
independent	146.4	157.3	188.3	216.6	282.8	373.2	628.2	787.1	1,046.3	1,212.2
TOTAL	**146.8**	**227.2**	**268.1**	**309.1**	**421.0**	**598.9**	**841.1**	**1,070.6**	**1,375.8**	**1,573.3**

Source: Own elaboration. Financial data retrieved from SABI Bureau van Dijk.

Incumbent banks did not stand still. A dilemma in the industry was whether traditional banks and FinTech companies should compete or cooperate, particularly in the face of a major threat – the big tech companies. To illustrate, the CEO of BBVA pointed out: "banks need to take on Amazon and Google or die" (González, 2013). They had already been leaders in the digitalisation process, with the two largest banks using online banking brands since the early 2000s (Uno-e by BBVA and Openbank by Santander, both merged with their respective owners nowadays).[4] And now, with the emergence of the FinTech firms, it is noticeable in Table 1 how the incumbent banks reacted after 2011, when Comercia Global Payments (the payment institution of Caixabank, the third largest bank) started to operate. Since then, the FinTech firms owned by banks or allied to them increased market share from 30.8% in 2011 (70.0 billion in revenue out of total industry revenues of 227.2 billion) to

[4] Former digital banks by BBVA and Santander, Uno-e and Openbank, are not considered in this research. These were brands inside their respective group, consequently lacking separate financial information. Moreover, keeping them out of the study is consistent with the focus of the analysis, which is observing the incumbent banks' reaction to the financial disruption brought by the fintech firms after the global financial crisis, with the launch of new FinTech ventures or setting alliances with existing ones.

37.7% in 2015 (225.7 billion out of 598.9 billion), followed by a decreasing trend afterwards – mostly due to a boom of independent firms in the payment and credit segments.

Following the above, we choose to limit our research in time and space: we focus on payment services and lending FinTech, which are the bulk of the industry,[5] during the decade of 2010s – before the impact of the 2020 pandemic, when a structural change is noticeable both in terms of GDP drop and the first increase in credit in more than one decade (see Figure 1). We seek to observe the degree of market competition over time, to answer the research question of whether FinTech owned by incumbent banks engaged in strategic interactions that differ from those of the independent FinTech, explaining competition.

2.2 Literature review on indicators of market competition

The dynamics of industry competition can be analysed by means of different structural and non-structural approaches. The structural approaches are based on the structure-conduct-performance (SCP) paradigm, according to which the market structure of an industry is exogenous and influences firm conduct, which in turn influences its performance. Under the relative-market-power hypothesis (Shepherd, 1982), firms with large market shares and differentiated products exercise market power and make higher profits. Simple indicators include the number of firms in the industry, measures of concentration ratio, and the **Herfindahl–Hirschman index (HHI)**.[6]

The SCP approach is compared with the efficient structure hypothesis (ESH), according to which firms with superior management or production technologies have lower costs and therefore obtain higher profits (X-efficiency, Demsetz, 1973), whilst other firms produce at more efficient scales and therefore have lower unit costs and higher unit profits (scale-efficiency, Lambson, 1987). This results in firms having larger market shares that may result in higher levels of concentration, but the profit-structure relationship is spurious (efficiency driving both profits and market structure). Neither SCP nor ESH explain bank profitability to a large extent (Berger, 1995), because the focus is on profits rather than the deviation of price from marginal cost, which is the correct basis for analysing competition (Paul, 1999).

Non-structural approaches, instead, are developed under the new empirical industrial organization (NEIO) approach. They provide theoretical models and assumptions on price and output determination to measure competition and assess market power based directly

[5] Crypto and blockchain firms are not included inside payment services, as in many instances they belong to commercial applications such as exchanges for virtual currencies or cannot be disentangled from the use of crypto as an asset (Bott and Milkau, 2016). Moreover, we did not trace any of those firms to be owned by banks, which limits their interest for this research.
[6] The concentration ratio is the sum of the market share held by the largest specified number of firms in an industry. Instead, the HHI is expressed as the sum of squared market shares of all firms (Kvålseth, 2018).

on firm conduct, comparing deviations between observed and marginal cost pricing without explicitly using any market structure indicator. Bikker and Bos (2005) explain that non-structural models, such as Panzar-Rosse and Bresnahan, as well as the SCP model, may be derived from the same framework. Here, each firm i maximizes profit π_i (depending on output vector Y_i, input vector X_i, output price vector p_i, and input price vector w_i) using a transformation function T and a pricing opportunity set H, capturing the firm's assessment of its competitive position. We may then define λ_i, the **conjectural variation** of firm i's output, as $\frac{dY}{dY_i} = 1 + \frac{d\sum_{j\neq i} Y_j}{dY_i} = 1 + \lambda_i$, such that a high λ_i means that firm i has a high awareness of its interdependence with other firms. Conversely, if firms are myopic (for example, they compete in Cournot or Bertrand fashion), their λ_i is zero. The result of the optimisation program, after rearranging for λ_i, would be:

$$\pi_i^* = p_i^* Y_i - w_i' Y_i X_i^* = \left[MS_i\left(-\frac{1}{\varepsilon_D}\right)(1+\lambda_i)\right] p_i^* Y_i \qquad (1)$$

Therefore, optimal profits π_i^* go up with an increase in market share MS_i, the conjectural variation λ_i, the price of outputs p_i^* and the demand Y_i, and a decrease in the price elasticity of demand ε_D. The different structural and non-structural models do a partial analysis and focus on a single right-hand variable in the equation, or a combination of two variables.

Early models derived are Iwata (1974) and the SCP model, which amounts to interpreting the combined impact of λ and HHI on performance under the equation (without control variables) $\pi^* = (HHI(1+\lambda))p^* Y$. The Bresnahan-Lau mark-up model (Bresnahan, 1982; Lau, 1982) provides a solution in terms of an equilibrium price equation that includes a mark-up not used under perfect competition, partly used under oligopoly or monopolistic competition, and fully used under monopoly (Bikker, 2003). In turn, the **Panzar-Rosse** (PR) model does not assume Cournot competition and works well with firm-specific data on gross revenues and factor prices, without needing information about equilibrium output prices and quantities for the firm and industry (Matthews *et al.*, 2007). Assuming $\varepsilon_D > 1$ and homogeneous cost structure, firms maximize profits when marginal revenue equals marginal cost. Market power is then measured by $\frac{\partial R_i^*}{\partial w_{k_i}}$, the extent to which a change in factor input prices (∂w_{k_i}) – where w is a vector of K input prices – is reflected in the equilibrium revenue (∂R_i^*) earned by firm i. The measure of competition, the Panzar-Rosse H statistic, is the sum of the elasticities of the reduced-form revenue with respect to the K input prices:

$$H = \sum_{k=1}^{K} \frac{\partial p^* Y}{\partial w_k} \frac{w_k}{p^* Y} \qquad (2)$$

The H statistic ranges between $-\infty$ and 1, with $H < 0$ implying that the market structure is a monopoly, $H = 1$ indicating perfect competition, and $0 < H < 1$ being associated with forms of monopolistic competition such as oligopoly.

Finally, beyond the basic framework by Bikker and Bos (2005) outlined above, two relevant indicators are the Lerner index and the Boone model. The **Lerner index** of market power (Lerner, 1934) highlights that relative margin (price minus marginal cost expressed as a percentage of price) is best for evaluating competition, since the gap between product price and marginal cost of production is the essence of monopoly power (Fernández de Guevara *et al.*, 2005). Thus, $LI = \frac{p - mc}{p}$, where p is the price of the good set by the firm and mc its marginal cost, and ranges $0 < LI < 1$, such that the higher the value the more the firm is able to price over its marginal cost, hence the greater its market power. However, the Lerner index and the H statistic as measures of market power face different theoretical and practical limitations (see Oduro *et al.*, 2022). In dealing with these limitations, recent studies use the **Boone indicator** (BI) by Boone (2008). The indicator compares the relative profit differences that result from differences in firm efficiency. Boone *et al.* (2005) explain this is most easily measured by $\hat{\beta}$ from a regression of the form

$$\ln \pi_i = \alpha + \beta \ln mc_i + \varepsilon_i \tag{3}$$

where π_i is the profit of each firm i, mc is marginal cost (the measure for efficiency), and β is the Boone indicator of market power – a profit elasticity that represents the percentage fall in firm's profit due to a percentage increase in its marginal cost. Since the marginal cost cannot be observed directly, Boone *et al.* (2005) approximate it with average variable costs (the ratio of labour costs and intermediates over revenues).

In our research, we use structural approaches (number of firms, concentration ratio and Herfindahl–Hirschman index), non-structural approaches (a conjectural variation model and the Panzar–Rosse H statistic), the Lerner index and the Boone indicator. Many recent articles on the market structure of the banking industry use any of these measures. The use of the HHI index is widespread, while a non-exhaustive list of recent articles using either the PR model or the Boone indicator would include Delis (2012), Arpegis et al. (2016), Léon (2016), Banya and Biekpe (2017), Khan et al. (2017), Ijaz et al. (2020), and Capraru et al. (2020) at the international level, and specific studies on countries such as Brazil (Barbosa et al., 2015). China (Tan, 2018; Fang *et al.*, 2019), Ecuador (Solano et al., 2020), Ghana (Oduro et al., 2022), India (Rakshit and Bardhan, 2019), Malaysia (Harkati et al., 2020), Nepal (Budhathoki et al., 2020), Thailand (Prayoonrattana et al., 2020), and Vietnam (Le and Vo, 2020). Conjectural variation models are frequently used in the literature of strategic management (Amit et al., 1988), while specifically oriented to the analysis of the banking industry we find models by Mas-Ruiz and Ruiz-Moreno (2017) in Spain, and Zhou *et al.* (2021) in China. Despite the extensive literature, we only trace one recent article specifically oriented to the analysis of market competition in the FinTech industry, in this case using the Panzar-Rosse model to analyse competition in Russia (Efimov *et al.*, 2021).

3. Methodology and hypotheses

3.1 Indicators of market competition

In this section, we analyse how market competition in the Spanish FinTech industry has evolved the last decade by means of the following indicators.

Four-firm concentration ratio (CR_4). This ratio follows from simply adding the market shares (MS) of the 4 largest firms in the industry:

$$CR_4 = \sum_{i=1}^{4} MS_{it} \tag{4}$$

where *i=1, … 4* are the largest FinTech firms by market share in an industry of *n* firms, and $MS_{it} = \frac{R_{it}}{\sum_{i=1}^{n} R_{it}}$ is the market share in terms of total revenue (R_{it}) of the *i*th firm on period *t*.

Herfindahl–Hirschman index of market concentration (HHI). Estimated by adding the squared market shares of all firms in the industry:

$$HHI = \sum_{i=1}^{n} MS_{it}^2 \tag{5}$$

Its value ranges $\frac{1}{n} \leq HHI \leq 1$. The minimum value, $HHI = \frac{1}{n}$, appears in industries where total production is shared equally among the *n* firms, while $HHI = 1$ is representative of a monopolistic industry whose revenues are concentrated in a single firm.

Panzar–Rosse H statistic. Defined as the sum of the elasticities of revenue with respect to a vector of K input prices (Eq. 2), market power is thus measured by the extent to which a change in factor input prices is reflected in the equilibrium revenue earned by firm *i*, ranging from monopoly ($H < 0$) to perfect competition $H = 1$.

Bikker and Bos (2005) argue that if the Panzar-Rosse model is to yield plausible results, firms need to have operated in long-term equilibrium (that is, the number of firms needs to be endogenous to the model). Consequently, we first test the long-term market equilibrium using the E-statistic, defined as the sum of input price elasticities from a dynamic profit equation specified as follows (Kumar and Gulati, 2018):

$$\ln(1 + ROA_{it}) = \alpha' + \lambda' \ln(1 + ROA_{it-1}) + \sum_{j=1}^{3} \beta'_j \ln w_{jit} + \sum_{k=1}^{6} \gamma'_k \ln Z_{kit} + \sum_{k=7}^{9} \gamma'_k \ln Z_{kt} + \varepsilon_{it} \quad (6)$$

where return on assets (ROA_{it}) is measured as profit after tax to total assets , w_j denotes the price of three inputs (labour, fixed asset, and financing), and Z_k is a vector of nine control variables, six of them for individual risks and costs (fixed asset ratio, capital ratio, provision ratio, an income diversification measure inspired by Laeven and Levine, 2007, as well as size and ownership following Oduro *et al.*, 2020, in order to have the same control variables as in the Boone indicator) plus other three industry and macroeconomic control variables (HHI, inflation and GDP growth). These variables are defined in Table 2.

Table 2. Study variables for competition in the FinTech industry.

INDICATOR	VARIABLE	CONCEPT	DESCRIPTION	DATA SOURCE
	n	number of firms	Number of all firms in the industry at year t	hand-collected data
CR4				
	CR4	4-firm concentration ratio	Sum of MS of 4 largest firms (in %)	
	MS	market share	Ratio of annual firm revenue over total industry revenues (in %)	Annual reports 2010 to 2019
HHI				
	HHI	Hirschman-Herfindahl index	Sum of squared MS of all firms	
PR H statistic				
	E	E statistic	Sum of β's of the 3 input factors in estimating ROA	Regression
	ROA	Return on assets	Ratio of profit after tax to total assets (in %)	Annual reports 2010 to 2019
	w_1	Price of labour	Ratio of personnel expenses to number of employees	Annual reports 2010 to 2019
	w_2	Price of fixed capital	Ratio of operating expenses excluding personnel to total assets	Annual reports 2010 to 2019
	w_3	Price of financing	Ratio of interest expenses to total liabilities (in %)	Annual reports 2010 to 2019
	Z_1	Fixed asset ratio	Ratio of fixed assets to total assets (in %)	Annual reports 2010 to 2019
	Z_2	Capital ratio	Ratio of shareholders' equity to total assets (in %)	Annual reports 2010 to 2019
	Z_3	Provision ratio	Provision to total assets (in %)	Annual reports 2010 to 2019
	Z_4	Income diversification	Financial and other operating income to revenue and all income	Annual reports 2010 to 2019
	Z_5	Size	Logarithm of total assets	Annual reports 2010 to 2019
	Z_6	Ownership	Binary 0 = independent, 1 = owned by incumbent banks	SABI
	Z_7	Inflation	Consumer price index based inflation rate	INE
	Z_8	GDP growth	Growth rate of real GDP	INE
	Z_9	HHI		
	H	H statistic	Sum of β's of the 3 input factors in estimating revenue	Regression
	R	Revenue	Total revenue	Annual reports 2010 to 2019
Boone				
	BI	Boone indicator	β of marginal cost in estimating profits	Regression
	π	Profits	Profit after tax	Annual reports 2010 to 2019
	mc	Marginal cost	Change in total cost caused by the increase in one unit of revenue	Separate regression
	c	Total cost	Sum of all operating expenses	Annual reports 2010 to 2019
	avc	Average variable cost	Ratio of operating expenses to revenue (in %)	Annual reports 2010 to 2019
Lerner				
	LI	Lerner index	Relative margin (P - mc) / P, data from conjectural variation model	Annual reports 2010 to 2019

Conjectural variation model

Q	Output	Sum of brands' online traffic in period t (proxied by Google Trends)	Annual reports 2010 to 2019
P	Output price	Ratio of total revenue by the n firms to total output Q	Annual reports 2010 to 2019
mc2	Variable cost per unit	Ratio of operating expenses to revenue scaled by P	Annual reports 2010 to 2019
N_B	IB's market share	Sum of the FinTech owned by incumbent banks' market share	
N_F	FF's market share	Sum of the independent FinTech firms' market share	
H_B	IB's squared weights	See defining equation in the text	
H_F	FF's squared weights	See defining equation in the text	
GDP	GDP	Gross domestic product in fixed prices	INE

The E-statistic is then defined as:

$$E = \sum_{j=1}^{3} \beta_j' \quad (7)$$

A Wald test is performed under the null hypothesis E = 0 of long-term market equilibrium. Otherwise, using a dynamic specification of the PR model is needed, since it accommodates the persistence of the dependent variable in competition determination. Then, the long-run H statistic is computed by estimating a reduced form of the log-normal dynamic function of the firm's revenue, specified as follows:

$$\ln R_{it} = \alpha'' + \lambda'' \ln R_{it-1} + \sum_{j=1}^{3} \beta_j'' \ln w_{jt} + \sum_{k=1}^{6} \gamma_k'' \ln Z_{kit} + \sum_{k=7}^{9} \gamma_k'' \ln Z_{kt} + u_{it} \quad (8)$$

where R_{it} is total revenue of the ith firm on period t, λ'' is the persistence coefficient, and the other variables are as explained above. Year fixed effects are added to control for the potential disruption effects of the financial and sovereign debt crises in Spain during the decade. To overcome endogeneity issues, a similar estimation strategy to that by Goddard and Wilson (2009) is employed, but using a two-step system GMM (generalized method of moments) approach with the lag of the explanatory variables as instruments rather than a first-difference GMM approach, as it provides more efficient estimators and reduces the potential biases of short time panels and in case of strong persistence in the lagged revenue variable (Blundell and Bond, 1998).[7] The long run (dynamic) H statistic is computed as:

$$H = \sum_{j=1}^{3} \beta_j'' \quad (9)$$

Boone indicator (BI). We follow Boone *et al.* (2005) for a simpler definition of the indicator, and Delis (2012) and Oduro *et al.* (2022) for an empirical model to estimate it. BI is thus defined as a profit elasticity representing the percentage fall in a firm's profit due to a percentage increase in its marginal cost, measured by $\hat{\beta}$ from this regression:

$$\ln \pi_{it} = \alpha + \beta \ln mc_{it} + \sum_{k=1}^{6} \beta_k \ln Z_{kit} + \sum_{k=7}^{9} \beta_k \ln Z_{kt} + \xi_{it} \quad (10)$$

[7] The overall validity of the instruments is tested by a Difference-in-Hansen test of exogeneity of instruments, and the assumption of serially uncorrelated errors is tested using Arellano–Bond AR(1) and AR(2) tests.

where π_i is the profit of each firm *i*,[8] mc is the marginal cost (the measure for efficiency), and Z_k is the same vector of nine control variables used in the PR model – here added to control for potential factors that affect the Boone indicator. A time dummy was introduced to control for the financial and sovereign debt crises.[9]

Since firms' marginal costs cannot be directly observed, Boone *et al.* (2005) approximate them with average variable costs. These are less complex but less accurate, because we cannot distinguish between variable and fixed costs, so in practice they are often proxied by average costs (Bikker and Van Leuvensteijn, 2008). We use this measure for robustness check only; as first option, we proxy the marginal cost of the FinTech firms from the trans log cost function specified below (Abel and Marire, 2021):

$$ln(c/w_3) = \alpha_0 + \alpha_1 \ln y + 1/2\alpha_2(\ln y)^2 + \alpha_3 \ln(w_1/w_3) + \alpha_4 \ln(w_2/w_3) + \alpha_5 \ln(w_1/w_3) \ln(w_2/w_3) + 1/2\alpha_6[\ln(w_1/w_3)]^2 + 1/2\alpha_7[\ln(w_2/w_3)]^2 + \alpha_8 \ln y \ln(w_1/w_3) + \alpha_9 \ln y \ln(w_2/w_3) + \varepsilon \quad (11)$$

The model assumes that the cost function (total cost, c) takes the form of a trans log cost function with one output (y) – representing revenue, R_{it} – and three input prices: of labour (w_1), of fixed capital (w_2), and of financing (w_3). The assumption of linear homogeneity in input prices is imposed by normalising total cost and input prices by one input price. The estimated coefficients of the cost function are then used in the calculation of the marginal cost as the derivative of the logarithm of total cost (c) over output (y):

$$mc = \frac{c}{y}\left[\alpha_1 + \alpha_2 \ln y + \alpha_8 \ln(w_1/w_3) + \alpha_9 \ln(w_2/w_3)\right] \quad (12)$$

To overcome possible endogeneity, we follow Oduro *et al.* (2022) in estimating the above equations using GMM, with 1-year, 2-year and 3-year lagged values of the explanatory variable, marginal costs, as instrumental variables.[10]

Lerner index (LI). Defined simply as the relative margin, it provides a value at firm level that is easy to interpret (a higher index value implies lower consumer welfare) and simple to estimate if information on product price and marginal costs is available. Following Cruz-García *et al.* (2018), a frequent empirical approach for the banking industry uses total assets to measure a bank's activity (since loans are the core of its business), estimates price as the

[8] Profits are normalized to positive numbers through a linear transformation.
[9] Year fixed effects were tried in first instance, but the GMM regression would not converge due to years 2017 to 2019 being omitted because of collinearity. Hence, a dummy variable *crisis* was introduced instead, such that crisis = 1 for years 2010 to 2013, and zero otherwise (year 2014 was the first one with positive real GDP growth).
[10] Marginal cost tends to weakly correlate with the first difference of the endogenous explanatory variable (Blundell and Bond, 1998). Moreover, if the lagged independent variable has no direct causal impact on the dependent variable nor the unobserved confounder, used as instrumental variable will mitigate the endogeneity problem by reducing bias and the mean squared error (Bellemare *et al.*, 2017). A test for overidentification of the instruments is performed using the Hansen J-test for GMM (Hayashi, 2000).

ratio of total revenues to total assets, and marginal costs as a trans log cost function similar to Eq. (11). However, for the FinTech firms in our sample – most of them being payments service providers, crowdlending platforms and comparators – this approach does not apply. Instead, price and marginal costs will be estimated using data from the conjectural variation model below, with price estimated at the industry level and individual marginal costs being proxied by the average variable cost per unit of revenue. This approximation provides a Lerner index for each firm, while the index at industry level is obtained as a weighted average of the individual indices, using revenues as weights (Cruz-García *et al.*, 2018).

3.2 A conjectural variation model for incumbent banks and independent FinTech firms

Conjectural variation models treat firm conduct as continuous-valued parameters to be estimated in terms of firms' conjectural variations – that is, their expectations about the reaction of other firms to an increase in quantity. Gollop and Roberts (1979) allowed conjectures to vary across firms, and Spiller and Favaro (1984) did the same in the banking industry to emphasize on heterogeneity of firm conduct (Bresnahan, 1989).

We use a model similar to that by Zhou *et al.* (2021) – who follow Spiller and Favaro (1984)'s model – adapted to explain competition between two groups in the industry: the FinTech ventures by the incumbent banks (B) and the independent FinTech firms (F). Assuming that these firms produce homogenous products or services, their demand function is $P_t = P(Q_t)$, where P_t is the price in period t and Q_t is the total quantity, $Q_t = \sum_{i=1}^{n} q_{it}$, for n firms in the market, where q_{it} is the output of the ith firm in period t (whether loans or other products and services). The first-order condition for profit maximization is

$$P_t + q_{it}\frac{\partial P_t}{\partial Q_t}\left[1 + \sum_{j\neq i}^{n} \frac{\partial q_{jt}}{\partial q_{it}}\right] - mc_{it} = 0 \qquad (13)$$

where mc_{it} is the marginal cost. The interaction between firms is assumed to depend only on their market shares (relative sizes), as

$$\frac{\partial q_{jt} q_{it}}{\partial q_{it} q_{jt}} = \beta_{it} + \gamma_{it} n_{it} \qquad (14)$$

where β_{it} and γ_{it} are parameters and $n_{it} = \frac{q_{it}}{Q_t}$ is the market share of the ith firm. Equation (14) indicates the expected reaction of firm *j* to firm *i*'s production change, a reaction that is related to firm *i*'s market share. Substituting Eq. (14) into Eq. (13), we get:

$$\frac{mc_{it}}{P_t} = 1 + \frac{1}{e}\left[n_{it} + \sum_{j\neq i}^{n} (\beta_{it} n_{it} + \gamma_{it} n_{it} n_{it})\right] \qquad (15)$$

where $e = \frac{\partial Q_t P_t}{\partial P_t Q_t}$ is the demand elasticity. The n equations for the n firms in (15) share one common variable, e, but assumptions are needed to simplify the estimation. Thus, with homogeneous interaction, all firms would have the same reaction to the production change of a firm, hence $\beta_{it} = \beta$ and $\gamma_{it} = \gamma$ for all *i, j*. Alternatively, if some group heterogeneity exists, in the sense that two groups of firms compete in the market, there would be different reaction functions within and between the two groups. For example, Spiller and Favaro (1984) distinguish a dominant group and a fringe group. The reaction functions between the two groups have significant differences, whereas firms in the same group face the same reaction functions. Thus, $\beta_{ki} = \beta_{kj}$, $\gamma_{ki} = \gamma_{kj}$; $i,j \in B$ or $i,j \in F$, and $\forall k$, $k \neq i,j$, where B and F represent the dominant group and the fringe group, respectively. This way, the $n \times (n-1)$ coefficients matrix can be simplified into eight representative coefficients, β_B^B,β_B^F,β_F^B, β_F^F,γ_B^B,γ_B^F,γ_F^B,γ_F^F, which are determined by reaction functions I to IV as follows:

$$\text{I:} \qquad \frac{\partial q_i q_j}{\partial q_j q_i} = \beta_B^B + n_j \gamma_B^B; \;\; i \in B, j \in B$$

$$\text{II:} \qquad \frac{\partial q_i q_j}{\partial q_j q_i} = \beta_F^B + n_j \gamma_F^B; \;\; i \in F, j \in B$$

$$\text{III:} \qquad \frac{\partial q_i q_j}{\partial q_j q_i} = \beta_F^F + n_j \gamma_F^F; \;\; i \in F, j \in F$$

$$\text{IV:} \qquad \frac{\partial q_i q_j}{\partial q_j q_i} = \beta_B^F + n_j \gamma_B^F; \;\; i \in B, j \in F$$

Reaction function I indicates the expected production change (reaction) of other Bs when Bj changes its production. Reaction function II indicates the expected production change of Fs in reaction to the production increase of Bj. Reaction function III represents the expected production change of other Fs in reaction to a change in Fj's production. And function IV represents the expected production change of Bs in face of that change by Fj. If an equation is above (below) zero, we expect retaliation (accommodation) from the other firms.

Substituting the reaction functions into the first order condition (Eq. 13), weighting the supply function by weights n_{it} and adding them up, we obtain the following equations:

$$\sum_{i \in B} \frac{mc_{it}}{P_t} \frac{n_{it}}{N_{Bt}} = 1 + \frac{1}{e} \begin{bmatrix} N_{Bt} H_{Bt} + \beta_B^B (N_{Bt} - N_{Bt} H_{Bt}) + \gamma_B^B \left(N_{Bt}^2 H_{Bt} - \sum_{i \in B} \frac{n_{it}^3}{N_{Bt}} \right) \\ + \beta_F^B (1 - N_{Bt}) + \gamma_F^B N_{Bt} H_{Bt} (1 - N_{Bt}) \end{bmatrix} \qquad (16)$$

$$\sum_{i \in F} \frac{mc_{it}}{P_t} \frac{n_{it}}{N_{Ft}} = 1 + \frac{1}{e} \begin{bmatrix} N_{Ft} H_{Ft} + \beta_F^F (N_{Ft} - N_{Ft} H_{Ft}) + \gamma_F^F \left(N_{Ft}^2 H_{Ft} - \sum_{i \in F} \frac{n_{it}^3}{N_{Ft}} \right) \\ + \beta_B^F (1 - N_{Ft}) + \gamma_B^F N_{Ft} H_{Ft} (1 - N_{Ft}) \end{bmatrix} \qquad (17)$$

where $N_{Bt} = \sum_{i \in B} n_i$, $N_{Ft} = \sum_{i \in F} n_i$, $H_{Bt} = \sum_{i \in B} \frac{n_{it}^2}{N_{Bt}^2}$, and $H_{Ft} = \sum_{i \in F} \frac{n_{it}^2}{N_{Ft}^2}$. Equations (16) and (17) are the supply functions of firms in group B and firms in group F, respectively.

Finally, the demand function of the industry takes the constant elasticity form (see Bresnahan, 1989) given by the equation:

$$\ln Q_t = e_0 + e \ln P_t + e_{GDP} \ln(GDP_t) + \varepsilon_t \quad (18)$$

where e is the demand elasticity, Q_t is outstanding output in fixed prices by the n firms, and GDP is the gross domestic product in fixed prices. Eqs. (16), (17), and (18) are the structure equations, with all of them sharing one common parameter, e. To avoid the endogeneity caused by the simultaneity bias, we use the three-stage least squares (3SLS) estimator to estimate the model.

Following Spiller and Favaro (1984), we pose the following hypotheses. First, a retaliation strategy (production increase) is expected by the dominant group – the FinTech owned by banks – when facing a production increase by another FinTech firm in the dominant group.

H1: *Reaction function I of any other firm i in the dominant group B to a change in production by firm j in the same group B will show a positive reaction, as given by* $\beta_B^B + n_i\gamma_B^B > 0$, $i \in B$.

In contrast, an independent FinTech firm would exhibit accommodation (decrease production) in response to a production increase by a firm owned by the incumbent banks.

H2: *Reaction function II of any firm i in the fringe group F to a change in production by a firm j in the dominant group B will show a negative reaction, as given by* $\beta_F^B + n_i\gamma_F^B < 0$, $i \in B$.

Third, one would expect no interaction among the independent FinTech firms.

H3: *Reaction function III of any other firm i in the fringe group F to a change in production by firm j in the same fringe group F will show no reaction, as given by* $\beta_F^F + n_i\gamma_F^F \approx 0$, $i \in F$.

Finally, some (little) retaliation (production increase) is expected from FinTech firms in the dominant group in response to a production increase by an independent firm.

H4: *Reaction function IV of any firm i in the dominant group B to a change in production by a firm j in the fringe group F will show a little retaliation, as given by* $\beta_B^F + n_i\gamma_B^F \geq 0$, $i \in F$.

In this framework, firms in the dominant group would have a certain level of monopolistic power and are scarcely influenced by the independent FinTech firms.

4. Degree of market competition in the Spanish FinTech industry

4.1 Sample

To assemble a comprehensive overview of the Spanish FinTech industry, we used a broad Internet search encompassing four steps. We started by retrieving a list of brands listed as FinTech firms in the main Spanish FinTech associations or identified as such in the existing

FinTech "radars".[11] Second, we enlarged the list with the directories of the respective national supervisory authorities,[12] and the census and sources recently provided by Banco de España (Sánchez and Quintanero, 2022). The third step consisted of screening and filtering out of potentially misclassified firms, through an individual analysis of their website, the business description there provided, contact information and other corporate information. This allowed to filter out a large list of companies that actually operate online from abroad, 44 brands for which we couldn't obtain any information about services provided or the company itself, and 45 firms that don't meet the definition by the Financial Stability Board of the Bank for International Settlements.[13] In case of doubt, we opted to classify them in the category of "other financial services". Finally, in a fourth step, we regularly updated the list from March 2021 to September 2022 with using news articles about FinTech in mainstream press and specialized sites,[14] and the information provided by some of the incumbent banks (mainly, Abanca Innova, Bankinter, and BBVA).

Our sample consists of a subset of this dataset: the 202 firms that operate in the segments of payment services (83) and credit (123) (some firms classified in both categories). Their financial statements from 2010 to 2019 were retrieved from SABI Bureau van Dijk database. It deserves mention that the financial reporting standards by financial institutions are different than those by ordinary firms – in Spain, in accordance with the regulations issued by the BdE.[15] However, all the FinTech firms in the sample are classified as ordinary firms. This implies that the calculation of indicators that make use of information provided by financial institutions – such as loans and deposits in the balance sheet and interest income and net interest income in the income statement – will require reformulation.

[11] Most firms were obtained at: AEFI – Asociación Española de Fintech e Insurtech (www.asociacionfintech.es), Finnovista radar (www.finnovista.com), and EFA – European Fintech Association (www.eufintechs.com/). Other directories include Universo Fintech, ACLE – Asociación de Crowlending Española,

[12] These include Comisión Nacional del Mercado de Valores (CNMV) for registries on dealer and brokerage services, as well as crowdfunding and crowdlending firms (plataformas de financiación participativa, PFP), Banco de España (BdE) for registries on credit financial institutions (entidades financieras de crédito, EFC), electronic money institutions (entidades de dinero electrónico, EDE), and payment institutions (entidades de pago), and the Dirección General de Seguros (DGS) on insurance companies. Furthermore, since 2020 the CNMV has regularly issued a series of warnings on entities that are providing financial services without authorisation. We have double checked these warnings, which include more than 2,000 companies (most of them foreigners), to identify additional FinTech firms. While mapping the whole universe of FinTech – and particularly, of crypto exchanges – is impossible, it ensures us that any Spanish crypto operator identified by the Spanish regulator has been included in the list.

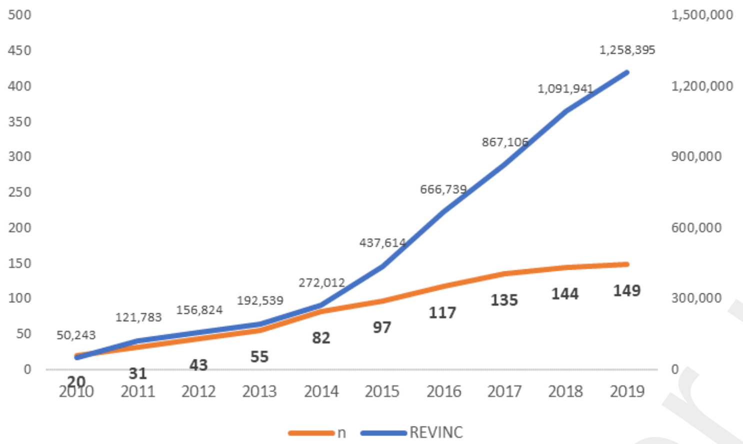
[13] Fintech firms are here defined as technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services. According to these, we have excluded from our database any comparators and platforms related to real estate investments, arts, and similar.

[14] Such as cointelegraph.com, finanzas.com, finnovating.com and spainfinancialcentre.com, among others.

[15] *Circular 4/2017 del Banco de España, a entidades de crédito, sobre normas de información financiera pública y reservada, y modelos de estados financieros*. Available at https://www.bde.es/bde/es/secciones/normativas/Regulacion_de_En/Estatal/Contabilidad.html

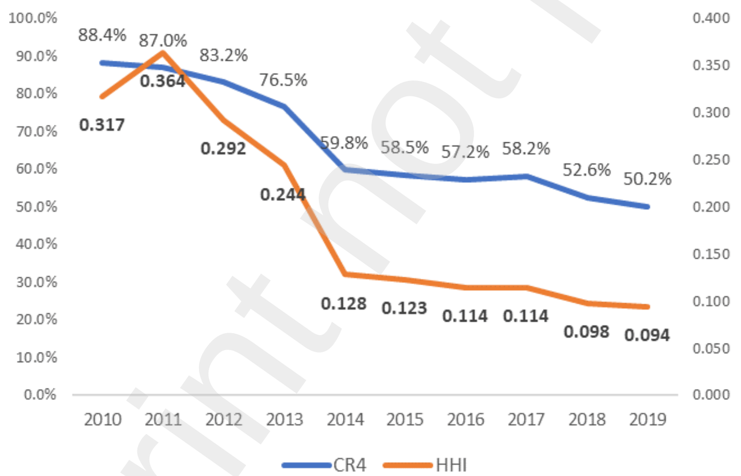
Figure 2 shows the boost of interest in payment services and credit FinTech firms, with 7 times more companies operating at the end of the period than early in the decade, and total revenues multiplying about 20 times – up to 1.35 billion euros in 2019. Strong revenue growth is observed from 2015 onwards.

Figure 2. Number of firms and total revenues in the industry, 2010-2019.



Next, we use the indicators of market competition described in Section 3. Figure 3 shows the CR_4 and the HHI of the industry.

Figure 3. Concentration ratio and HHI index in the industry, 2010-2019.



Both indicators point out to a decreasing concentration in the context of the emergence of new competitors in the industry. Thus, the four largest competitors had more than 80% of the market share in years 2010 to 2012, only to decrease to CR_4 ratios in the range of 55-60% in 2014 to 2017 and falling to 50% afterwards. The largest competitor accounted for 57.1% of the revenues in 2011, decreasing to 28.4% in 2014 and falling below 21.0% in 2019. This is similar to the information provided by the HHI index, with a steep drop from

2011 to 2014, when the index fell from 0.36 to 0.13. The trend moderated thereafter but has continued to decrease steadily to a value of 0.09 in 2019. All these values are in any instance representative of an atomised industry.

4.2 Results by indicator

In this section we measure the Panzar-Rosse H statistic, the Boone indicator, and the Lerner index. Table 3 provides descriptive statistics for the variables used. Data is winsorised at the 1% and 99% for all continuous regressors, with 873 year-firm observations available (after any observations with zero revenues were discarded).

Table 3. Descriptive statistics, 2010-2019.

Variable	N	Mean	std.dev.	min	p25	median	p75	max
n	873	111.36	38.27	20.00	82.00	117.00	144.00	149.00
MS	873	0.01	0.05	0.00	0.00	0.00	0.00	0.57
ROA	857	-21.95	47.41	-281.10	-33.80	-7.10	2.60	55.70
w1	719	36.40	18.56	1.76	23.97	33.22	45.73	118.68
w2	860	0.82	1.09	0.03	0.25	0.51	0.98	10.85
w3	862	1.72	3.22	0.00	0.00	0.50	2.10	33.50
Z1	865	35.78	29.86	0.00	6.90	30.90	62,70	98.00
Z2	866	25.08	50.46	-100.00	2.40	30.50	64,10	99.10
Z3	861	0.25	2.81	-0.20	0.00	0.00	0.00	42.70
Z4	865	15.08	20.49	-1.09	0.00	1.39	35.28	50.00
Z5	857	6.61	2.00	1.84	5.37	6.48	7.69	12.83
Z6	873	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Z7	873	0.94	0.96	-1.00	0.30	1.10	1.20	3.00
Z8	873	1.84	1.81	-3.36	1.60	2.22	3.12	4.09
Z9	873	0.14	0.07	0.09	0.10	0.11	0.13	0.36
R	857	4,193.4	12,638.5	0.16	67.13	331.10	1,497.5	86,801.0
profit	856	31.01	1,809.5	-6,257.1	-198.36	-22.09	19.45	17,122.0
cost	857	3,977.4	10,934.7	4.34	149.96	511.46	1,784.5	76,401.6
avc	857	7.81	36.53	0.23	0.95	1.15	2.52	574,07
price	873	0.22	0.06	0.17	0.20	0.20	0.22	0.43

For the **PR model**, we first test the E-statistic for long-term market equilibrium. The results of the 2-step GMM are provided in Table 4.

The E-statistic, the sum of the β_j' in the regression, is $E = -0.067$, and the Wald test shows it is different from zero ($chi^2(1)$ 6.93, p=0.008), implying long-term market disequilibrium. Hence, a dynamic specification to estimate the H statistic is required to accommodate the persistence of the dependent variable in competition determination. Arellano–Bond tests of the assumption of serially uncorrelated errors yield p<0.05 for first-order autocorrelation (AR1) and p>0.1 for second-order autocorrelation (AR2), as expected.[16]

[16] Following Roodman (2009), we collapsed instruments to limit instrument proliferation and improve the power of the Hansen test. The rule of thumb of groups (149) largely outnumbering instruments (26) is satisfied.

Table 4. PR model: E-statistic and H-statistic. Two-step system GMM, 2010-2019.

dependent	**lnROA**			
Coefficients	Coef.	Std.Err.	z	
lnROAlag1	-0.0012	0.0527	-0.02	
w1	-0.0023	0.0022	-1.04	
w2	-0.0362	0.0245	-1.48	
w3	-0.0286	0.0089	-3.21	***
Z1	-0.0076	0.0018	-4.19	***
Z2	0.0056	0.0013	4.25	***
Z3	0.0044	0.0037	1.19	
Z4	0.0026	0.0024	1.07	
Z5	0.0744	0.0554	1.34	
Z6	-1.0728	0.8468	-1.27	
Z7	-0.0171	0.0188	-0.91	
Z8	-0.0352	0.0197	-1.79	*
Z9	-0.7259	0.6818	-1.06	
const	-0.27	0.55	-0.48	
Model statistics				
N. observ.	575	Wald chi²	120.7	***
N. groups	149	AR(2)	-0.33	
N. instrum.	26	Sargan chi²	35.0	***
		Hansen chi²	17.2	
Long-run market equilibrium test				
E statistic	-0.0672			
H_0: E = 0	6.93	chi² (1) p-va	0.008 (Disequil.)	

dependent	**lnR**			
Coefficients	Coef.	Std.Err.	z	
lnRlag1	0.0326	0.0344	0.95	
w1	-0.0062	0.0060	-1.03	
w2	0.5463	0.1189	4.59	***
w3	0.0305	0.0207	1.48	
Z1	0.0076	0.0039	1.97	**
Z2	0.0021	0.0021	1.01	
Z3	0.0001	0.0080	0.01	
Z4	0.0056	0.0044	1.29	
Z5	1.3700	0.0911	15.04	***
Z6	2.0848	3.0358	0.69	
Z8	-0.0170	0.0487	-0.35	
Z9	-0.5568	2.1478	-0.26	
year fixed effects				
const	-4.11	0.95	-4.33	***
Model statistics				
N. observ.	654	Wald chi²	7,440.5	***
N. groups	158	AR(2)	0.55	
N. instrum.	38	Sargan chi²	97.7	***
		Hansen chi²	15.8	
Test for competitiveness				
H statistic	0.5707	(Monopolistic competition)		
H_0: H = 0	22.10	chi² (1) p-val	0.000 (no monopoly)	

Notes: GMM with collapsed instruments. * significant al 10%; ** significant at 5%; *** significant at 1%.

The Panzar-Rosse H statistic is then estimated. Measured as the sum of the β_j'' in the regression, its value would be $\boldsymbol{H = 0.57}$ with collapsed instruments and year fixed effects.[17] Being in the range of $0 < H < 1$, it suggests some form of monopolistic competition in the industry. Again, Arellano–Bond tests yield p=0.07 for AR1 and p>0.1 for AR2, as expected.

Next, we estimate the **Boone indicator**. First, we compute the marginal costs of each bank and year by estimating the trans log cost function in Eq. (11), and substituting the parameter estimates in Eq. (12) to get the marginal cost. Then, the indicator is estimated with a GMM regression, with 1-year, 2-year and 3-year lagged marginal costs as instrumental variables. A dummy variable was used to control for crisis years of 2010 to 2013. The results are provided in Table 5. The value of the indicator is $\boldsymbol{BI = -1.61}$ among firms with positive profits, but $\boldsymbol{BI = -0.42}$ if all firms are included (profits normalized to positive numbers).[18] Following Delis (2012), higher (less negative) values of the BI indicator indicate higher levels of market power, with average values usually ranging between -2.0 and -4.0 in high income countries. Hence, our results suggest a low degree of competition among profitable

[17] Again, the number of groups (158) largely outnumbers instruments (38) after collapsing.
[18] Hansen J-test required introducing one of the lagged variables in the model for it to be correctly specified.

companies, and very high market power of these firms relative to those in the Spanish FinTech industry facing losses. Still, only the result for all firms is robust to using average costs as a proxy for the marginal cost, with competition among profitable firms being much fiercer (higher than 4.0) if average costs are used.

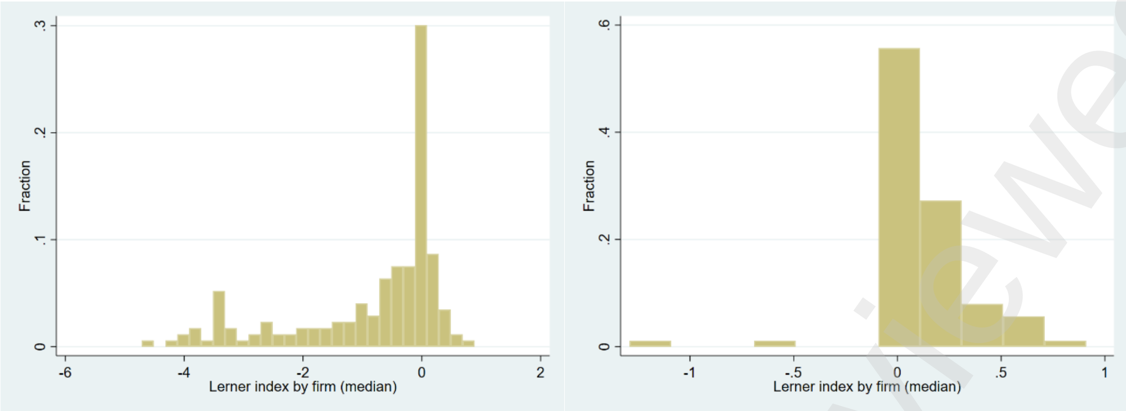
Table 5. Boone indicator. Two-step system GMM, 2010-2019.

dependent	ln profit			
Coefficients	Coef.	Robust Std.Err.	z	
ln mc	-1.6070	0.6162	-2.61	***
ln mc lag3	1.5902	0.3161	5.03	***
Z1	-0.0081	0.0052	-1.54	
Z2	0.0155	0.0064	2.44	**
Z3	0.0523	0.0127	4.13	***
Z4	-0.0046	0.0141	-0.33	
Z5	0.5821	0.1657	3.51	***
Z6	1.3597	0.7878	1.73	*
Z7	0.2352	0.2237	1.05	
Z8	0.5361	0.1922	2.79	***
Z9	-9.9783	6.7996	-1.47	
crisis	1.9889	1.4883	1.34	
const	-7.70	1.87	-4.11	***
Model statistics				
N. observ.	77			
Hansen's J-test chi^2	0.858	J-test sig	0.354	

Note: * significant al 10%; ** significant at 5%; *** significant at 1%.

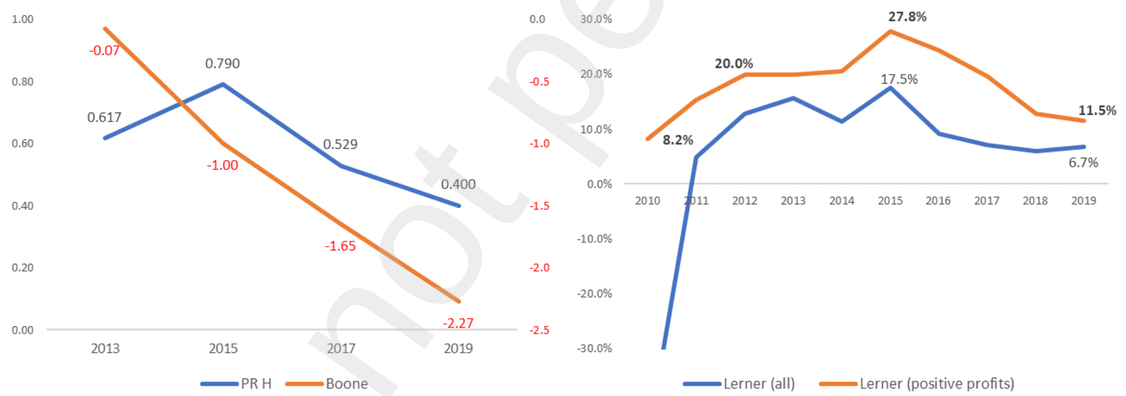
Consequently, we use the **Lerner index** to complement the interpretation. Since this index can be estimated at individual level, it helps to understand why we might be seeing vague results: for many firms, being profitable is, for the time being, a pipe dream. The histogram to the left-hand side of Figure 4 shows that a large proportion of firms exhibit negative relative margins. These in many cases are startups with large investments and operating expenses after launching, but very low revenues. Still, the large negative values observed might be a result of how marginal costs were proxied (as the ratio of operating expenses to revenue scaled by the price). When only firms with positive profits are considered, near 90% of them show Lerner indices between 0 and 0.4 (histogram to the right-hand side). In this case, the index at industry level during the decade, obtained as a weighted average of the individual indices using revenues as weights, is $\boldsymbol{LI = 17.0}\%$ (8.0% if year-firms with negative profits are also included). This compares relatively low to the Lerner index for banks in Spain, usually in the range of 30-40% (Cruz-García *et al.*, 2018), suggesting a lower market power of FinTech firms.

Figure 4. Histogram of individual Lerner indices, median values for 2010-2019.



An analysis of the evolution of market power may provide some additional insight. Figure 5 shows the performance over time of *H* statistic and Boone indicator (LHS) and Lerner index (RHS, for all firms and firms with positive profits compared). This is intended mostly for descriptive purposes, since *H* and *BI* had to be estimated with robust OLS regressions for groups of three years (due to the reduced number of observations per year).

Figure 5. Market power over time, 2010-2019.



The Lerner index is quite stable in the range of 10-30%, with a nuance. Thus, it shows that many firms struggled to achieve positive returns during the crisis, while competition after 2015 largely reduced profitability. The Boone indicator provides a similar intuition, with a trend of increasing competition over time. The low levels of competition we obtained above for the complete sample may be driven by the impact of the crisis, when the indicator values might not be quite representative (there were few firms, most of them running losses). More recently, the value is near -2.5, suggesting moderate competition. The H indicator suggests monopolistic competition as well (often ranging 0.4-0.6), but the peak of competition is instead observed by 2015 (when a strong revenue growth was observed in the industry, according to Figure 2). The trend shown by the Boone indicator and the Lerner index would be consistent with trend by the structural measures (CR_4 and HHI), while the peak by the *H* statistic coincides with the sharpest decrease of the structural measures in 2014. To sum up, the overall picture by all indicators combined seems to suggest a sharp reduction in concentration after 2014, but only moderate levels of competition during the decade.

5. Strategic interaction in the Spanish FinTech industry

Once we characterised overall market competition among FinTech firms of any kind, now we use the conjectural variation approach described in Section 3 to answer the question of whether FinTech and traditional banks compete or collaborate. We model the interaction between two groups – incumbent banks (through their FinTech interests) and independent FinTech firms. We identify as incumbent banks (B) any FinTech firms owned by or allied to incumbent banks (treatment group = '*incumbent*'), and the other firms as independent FinTech firms (F). For robustness, we also test the model using as firms in the treatment group only those exclusively owned by incumbent banks (treatment group = '*owned*').

Following Zhou et al. (2021), total industry output (Q) would be the sum of any financial products provided by a banking sector to customers. Usually proxied as total loans in the industry,[19] for FinTech firms we must accommodate this measure to their reality. Thus, a proxy is needed that accounts for the services provided by a heterogeneous mix of payments services providers, crowdlending platforms, comparators, etc. Here we suggest using the sum of the online traffic every year by all the FinTech brands. As proxy, we use Google Trends as measure of the popularity of the brands in Google Search in Spain every year, to obtain an annual estimate for the industry output. The output price (P) of the industry is hence estimated annually as the ratio of the sum of total revenue by the n firms to total output Q, interpreted as the average price for the services provided at the industry level. An individual estimate of the marginal cost is proxied by the average variable cost per unit of revenue (mc2), measured as the ratio of operating expenses to total revenue scaled by P.

Considering *incumbent* as treatment group, we regress the simultaneous equations model provided by Eqs. (16), (17), and (18) with the 3SLS estimator. Since Eqs (16) and (17) are added up at the cross-sectional level, despite having 202 firms the resulting regressions are underidentified for 10 annual observations and 12 parameters overall. To overcome this, we have interpoled data between each pair of annual observations. The resulting regression coefficients – provided in Table 6 – are almost identical to those obtained by regressing the

[19] In a model à la Zhou *et al.* (2021) of banks providing loans only, the output price would be estimated as interest income to total loans. Here, FinTech firms operate in different segments other than credit supply and, what is more relevant, information in the annual reports is provided in the regular format, without specifying loans, deposits or interest income. Hence, we an alternative measure will need to be specified.

identical cross-sectional data for all firms in the database (coefficients that would be more precise for the real data available but unsuitable for hypothesis testing).

Table 6. Conjectural variation model: parametric estimation, 2010-2019.

Treatment group: Incumbent

Equation 1: Incumbent banks			**Equation 2: independent FinTech**			**Equation 3: demand function**		
Coefficient	Estimate	Std. Err.	Coefficient	Estimate	Std. Err.	Coefficient	Estimate	Std. Err.
β_B^B/e	4.5	0.4762 ***	β_F^F/e	0.8	0.8722	e	-2.4	0.2560 ***
γ_B^B/e	-19.2	2.6265	γ_F^F/e	-38.1	22.426 *	e_0	-43.8	7.3536 ***
β_F^B/e	0.0	0.0000 ***	β_B^F/e	0.0	0.0000	e_{GDP}	10.4	1.6252 ***
γ_F^B/e	5.4	1.0423 ***	γ_B^F/e	-18.6	9.1576 **			

Treatment group: Owned FinTech

Equation 1: Incumbent banks			**Equation 2: independent FinTech**			**Equation 3: demand function**		
Coefficient	Estimate	Std. Err.	Coefficient	Estimate	Std. Err.	Coefficient	Estimate	Std. Err.
β_B^B/e	5.8	0.9828 ***	β_F^F/e	0.3	0.4933	e	-2.4	0.2604 ***
γ_B^B/e	-41.8	6.1238 ***	γ_F^F/e	-14.1	7.2310 **	e_0	-40.9	7.4594 ***
β_F^B/e	0.0	0.0000	β_B^F/e	0.0	0.0000	e_{GDP}	9.8	1.6496 ***
γ_F^B/e	8.5	1.0850 ***	γ_B^F/e	-5.7	2.3234 **			

Note: * significant al 10%; ** significant at 5%; *** significant at 1%.
Equation 1 and Equation 2 include $\sum_{i\in B}\frac{mc_{it}}{P_t}\frac{n_{it}}{N_{Bt}}$ and $\sum_{i\in F}\frac{mc_{it}}{P_t}\frac{n_{it}}{N_{Ft}}$ as dependent variables, respectively.
Standard errors presented in the table are robust.
B, the FinTech interests of incumbent banks. F, the independent FinTech firms.

Table 6 shows a demand elasticity of −2.4 (a negative relationship between demand and price consistent with our expectations). Most coefficients in the three equations are tested significant; however, they are not the relevant ones to interpret; we need to test the four reaction functions to investigate the interactions between the FinTech owned by banks and the independent FinTech. To obtain the reaction functions I to IV we proceed as follows:

- We solve for βs and γs in reaction functions I & II using Eq. (16) results solving for elasticity e estimated in Eq. (18). Then, we estimate the reaction functions for a given market share n_j. The results are provided in Table 7 for market shares of 90th, 75th, 50th, 25th and 10th percentiles from each group of firms that are forming conjectures.
- We do the same for βs and γs in reaction functions III & IV using Eq. (17) solving for the elasticity e estimated in Eq. (18), and then estimate the reaction functions for different market shares n_j.

The results, provided in Table 7, are identical whether we include as treatment firms those that are either owned by or allied to banks or only those that are owned. Moreover, most results are consistent for different market shares of both groups of competitors. We find that, first, all firms adopt a retaliation strategy when coping with a production increase by another firm in the same group, whether this is a FinTech owned by an incumbent bank (hypothesis H1) or an independent one (hypothesis H4). The effect is stronger the larger the market share of peer competitors. Second, the independent firms show accommodation in response to a production increase by a FinTech owned by a bank (hypothesis H2). However, and contrary to hypothesis H3, the group of FinTech firms owned by banks do exhibit some degree of retaliation if an independent firm increases production – suggesting competition rather than collaboration by the incumbent banks.

Table 7. Hypothesis testing of the reaction functions, 2010-2019.

Treatment group: Incumbent

Reaction fn.						
I	-1.1 ***	0.1	2.2 ***	4.2 ***	5.4 ***	Favour H1 (>0)
	0.00	0.14	0.00	0.00	0.00	
II	-0.2 ***	-0.6 ***	-1.1 ***	-1.7 ***	-2.0 ***	Favour H2 (<0)
	0.00	0.00	0.00	0.00	0.00	
III	14.1 **	11.7 *	7.7 *	3.7 *	1.3 *	Against H3 (≈0)
	0.04	0.08	0.09	0.09	0.10	
IV	7.0 *	5.9 *	3.9 *	2.0 *	0.8 *	Favour H4 (>0)
	0.05	0.05	0.05	0.05	0.05	
market share n_j (B)	**10%**	**25%**	**50%**	**75%**	**90%**	
market share n_j (F)	90%	75%	50%	25%	10%	

Treatment group: Owned FinTech

Reaction fn.						
I	-0.7 ***	1.9 ***	6.3 ***	10.6 ***	13.2 ***	Favour H1 (>0)
	0.00	0.00	0.00	0.00	0.00	
II	-0.4 ***	-0.9 ***	-1.8 ***	-2.7 ***	-3.2 ***	Favour H2 (<0)
	0.00	0.00	0.00	0.00	0.00	
III	5.2 ***	4.3 **	2.8 **	1.3 **	0.5 **	Against H3 (≈0)
	0.00	0.02	0.04	0.04	0.05	
IV	2.1 **	1.8 **	1.2 **	0.6 **	0.2	Favour H4 (>0)
	0.02	0.01	0.01	0.01	0.01 **	
market share n_j (B)	**10%**	**25%**	**50%**	**75%**	**90%**	
market share n_j (F)	90%	75%	50%	25%	10%	

Note: * significant al 10%; ** significant at 5%; *** significant at 1%.
p-values are tests of Prob > chi2 for the null hypothesis of the reaction functions being equal to zero for that specific sum of market shares n_j(B) and n_j(F).
B, the FinTech interests of incumbent banks. F, the independent FinTech firms. Market shares indicate that we selected those percentile FinTech firms, respectively, from the group of Bs or Fs, to form the conjecture.

6. Conclusions

Our research delved into the reaction of traditional banking to the emergence of a new competitor on a global scale – the financial technology firms. Using the Spanish FinTech industry as a case study, we sought to answer a question frequently asked in the industry: do FinTech firms and incumbent banks compete or collaborate?

We provided an analysis of market competition among payment services providers and credit FinTech during the decade of 2010s. The context is of strong growth, with seven times more firms at the end of the period than early in the decade, and total revenues increasing more than twentyfold. The HHI index and concentration ratios show sharp reductions in concentration, particularly from 2011 to 2014, leading to a highly atomised industry. Still, the measures of market power (Panzar-Rosse H statistic, Boone indicator and Lerner index) suggest only moderate levels of competition – though often increasing recently. However, when the analysis is performed by means of an oligopolistic conjectural variation model that allows to test competition between banks (through the FinTech ventures owned by or allied to them) and the independent FinTech firms, a different picture emerges: our model shows that strategic interactions exist between and within the two groups of firms, with a clear pattern of competition rather than collaboration by the incumbent banks.

Comparing our results against the existing literature, it is noteworthy that, despite the widespread use in the academic literature of structural and non-structural approaches to characterise competition in banking industries, both domestically and internationally, we only trace one recent article specifically oriented to the analysis of market competition in the FinTech industry (Efimov et al., 2021, for the Russian market). Still, we may relate our results to those obtained by Wang et al. (2021), who have recently shown how the development of FinTech has exacerbated banks' risk taking in China. Perhaps this is due to the novelty of the topic and lack of sufficient data, so future research should help characterize the reaction of the banking sector to the irruption of FinTech. The topic is of interest to authorities, who may draw lessons for policymaking in the context of current debates such as the impact of the European PSD2 regulation on banks of the potential disruptive effect of CBDCs over the banking sector.

Our study still shows some limitations, such as those imposed by lack of quarterly financial data for private companies in Spain, or the need to proxy total output of the industry through an estimate of their annual online traffic. Future research might try to overcome these limitations, as well as linking patterns of market competition to key drivers of FinTech success (see Hua and Huang, 2021) or identifying which actors are doing more for financial inclusion (see Demir et al., 2022). Moreover, being FinTech a sector intensive in technology and human capital, future research might explore the use of a different production function to obtain the measures of competition, one in which IT capital and human capital is used instead of capital input measured as fixed assets to total assets. Beyond that, the well-known limits of using concentration as a measure of competition should be considered.

Declaration of interest

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