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Bank market power and performance of financial technology firms

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Abstract

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Keywords: Financial technology, Bank market power, Competition, Firm performance, Lerner index, Boone index.

JEL Classification Numbers: L11, G21, G23. L25.

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1. Introduction

Financial technology (fintech) firms operate outside the traditional business models of financial services by combining technology with finance (Mention, 2019, Gabor and Brooks, 2017, Eickhoff et al., 2017). These are new and emerging firms entering the financial sector. Using technological advancements such firms introduce services that are more accessible and cost-effective directly competing with the ones provided by traditional banks. They also have a “disruptive” role within the market, spearheaded by entrants offering new products and services using innovative technologies (Aaker and Keller, 1990; Christensen, 2003; Milian et al., 2019).

The evolution of the relationship between fintechs and banks during the last decade is not yet well understood or established empirically (Li et al. 2017; Phan et al. 2020). Nguyen et al. (2021) use macroeconomic panel data on seventy-three countries during a five-year period to study the impact of fintech credit on the performance of banks. They find that fintech credit reduces bank profitability but may positively influence bank stability (through risk) if bank regulations in the country become stricter.

The purpose of our paper is distinct and separate from the existing theoretical and empirical literature to this date (the latter is discussed at some length in the next section). We seek to empirically establish whether there is a causal link between the performance of fintech firms and changes in the market power of banks in that country, and if so whether such a link is positive or negative. The traditional approach in Industrial Organisation is to investigate the impact of an industry’s market structure on its performance, at the industry level. Instead, we establish a relationship between the performance in one industry (fintech firms at the firm level) as determined by market power in another industry (bank concentration at the industry level). Therefore, we adopt a structure-conduct-performance approach *between* two distinct industries rather than *within* an industry.

Given the difference in approach, we do not expect a priori the positive relationship found in the literature (which is briefly summarised in the next section) on the impact of market structure *within* an industry on the performance of the firms that operate within that same industry. Rather, the relation can be in either direction. Positive, if fintechs and banks operate as offering complementary services since the increasing market power of banks will enhance their performance, and in turn complement fintech services. If, on the other hand, such services are viewed as substitutes, then the two groups would be directly competing for customers. As a result, the increase in the bank market power would enhance the performance of banks at the expense of the performance of fintechs leading to a negative relationship. While the emerging literature discusses complementarity and substitutability between banks and fintechs, no other study follows a structure-conduct-performance approach. Hence, we are filling an important gap in the emerging fintech literature.

An additional distinct feature of our approach is that the fintech performance variable in our model is at the firm level. While the common practice in the Industrial Organisation literature (see Section 2) is that the fintech performance variable is at the industry (three or four-digit) level. Hence, we look at the micro-foundations of studying the competition between fintechs and the banking sector in our empirical analysis.

For benchmarking purposes, our study uses 231 fintech and 231 non-fintech firms from six industries across twenty-four industrialised countries. Hence, we empirically assess the impact of changes in bank market power on the performance of non-fintech firms as well. We use the six industries where fintech firms are typically found operating: Capital Markets, Professional Services, Consumer Finance, Software, IT Services and Banks. The twenty-four industrialised countries in this study include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong (HK), Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Sweden, Singapore, South Korea, Spain, Switzerland, United Kingdom (UK) and United States of America (US).

In the next section, we briefly review the existing relevant literature and lay out our hypotheses. Section 3 offers the empirical specification. Section 4 discusses the sample and the summary statistics. Section 5 offers the empirical results. Section 6 tests the robustness of our results. The concluding section of the paper discusses the implications of our results.

2. Related Literature and hypothesis development

There is a well-established literature in Industrial Organisation (IO) on the structure-conduct-performance (SCP) paradigm (Bain, 1951), where the causality runs from structure (more concentrated industries) allowing more collusive conduct which leads to performance (higher profits and prices), thus establishing a positive relationship. The alternative to this approach is the differential efficiency hypothesis (DEH). The DEH which contests the SCP's presumed causality by arguing that it is the more efficient firms that are rewarded with both higher profits and market share, leading to an increase in market consolidation at the industry level reflected by high market power and concentration (Demsetz, 1973; Peltzman, 1977; Gale and Branch 1982).

A multitude of empirical studies during the 1970s and 1980s estimate simple theoretical models testing for the positive relationship between industry-level concertation and performance by focusing mostly on manufacturing industries at the three, and more occasionally four, digit level (Weiss, 1971; Bresnahan and Schmalensee, 1987; Bresnahan, 1989). While both the SCP and the DEH point to such a positive relationship between performance and market structure, they clearly have diametrically different implications for competition policy (Gale and Branch, 1982; Baumol et al., 1982; Chortareas et al., 2011; Seelanatha, 2010). While an antitrust approach by competition authorities on large firms would be appropriate in the former case, it would clearly have deleterious implications on efficiency if DEH was at work, as it would punish superior efficiency. Consequently, there is a need to add to the SCP regressions of the impact of concentration and market share on performance, and control variables that explicitly allow for both x-efficiency as well as scale efficiency (pure and pseudo efficiency respectively in IO terminology).

The prediction of a positive relationship between performance (profits or return on assets) and market structure, and whether this stems from increased market power or from differences in efficiency among companies, has also been studied extensively in the banking industry (see, for example, Evanoff and Fortier, 1988). It has been studied by testing both the SCP paradigm and the DEH hypothesis in different countries (for example, Smirlock, 1985; Berger and Hannan, 1997; Berger, 1995; Maudos, 1998; Bikker and Haaf, 2001; Shaffer, 2004; Goddard et al, 2007; Chortareas et al., 2011; Fu and Heffernan, 2009; Delis and Tsionas, 2009). Berger and Hannan empirically use four different approaches in the literature to distinguish between the SCP paradigm and the DEH in banking. These include the simple regression of profits on market structure and market shares, including proxies for scale efficiency, using survey information on prices instead of profits as the dependent variable, and finally directly relating market structure to efficiency by regressing the former on efficiency measures.

As we mentioned in the introduction, fintech innovations can transform services, products, and market segments (Gulamhuseinwala et al., 2015). As such, they are expected to have an impact on revenue, costs, and profit margins in both the fintech as well as in the traditional financial sector. Hence, fintech alters the dynamics of the financial industry and ultimately affects the mode of competition within the financial industry (Eckenrode and Srinivas, 2016). It is to this point that we turn our attention to formulating the relationship between banks and fintechs in the last decade.

From a marketing perspective, the relationship between fintechs and banks so far can be described as one of coopetition (Anand and Mantrala, 2019). The typical response from banks has been to collaborate with such firms rather than attempt to acquire them or directly compete with them. (Ntwiga, 2020) This lack of interest by banks in buying such companies may be a combination of three things. First, a limited history of stability and financial recording on the side of the fintechs makes the process of due diligence tricky. Second, the risk of integrating a fintech within the organisational structure of a bank given the large operational and cultural differences between the two entities. Finally, strict banking regulations govern the credit processes of banks.

From an industrial organisation perspective, fintech firms can act as substitutes to banks if they serve the same customers or as complements serving different segments (Tang, 2019). Tang tests the relationship by using the impact of regulatory supply shocks in the banking industry and finds that P2P firms both substitute and complement banks in small loans. Focusing on the demand side, Braggion et al. (2020) show that borrowers perceive such firms as complementary sources of finance to secure a bank mortgage. Specifically, borrowers respond to regulatory changes in the size of the required mortgage deposit by altering the size of their borrowing from P2P lenders if their own assets at hand are not sufficient. The relationship is tested by looking at regulatory supply shocks in banking that take the form of changes in the size of the required mortgage deposit, and how such changes affect the size of such clients borrowing from P2P lenders if their own assets at hand are not sufficient.

More generally, customers will consider the services offered by fintechs as an addition to, or as a substitute for, the services offered by banks. We would see this reflected by a respectively positive or negative link between the banks' market power and the profitability of fintechs. In other words, while we expect a link between the banks' market structure and the profitability of fintechs, this may result from the fintechs' services being either a complement or a substitute to the services offered by banks. Therefore, the degree of changes in the market power of banks will affect the performance of fintechs, although the direction, positive or negative, of the impact is ambiguous. We set out to explore this relationship by setting our hypothesis and subsequently empirically answering this question below.

2.1. Impact of Bank Market Power

Based on the discussion in the Introduction and the overview of the related literature, we formulate the hypothesis that changing market power in the banking sector will affect the performance of fintech firms and non-fintech firms.

We consider separately two alternative measures of bank competition, the Lerner index, which is based on the deviation between price and marginal costs, and the Boone Index. For reasons discussed below, we prefer the Lerner index, but the Boone index (Boone, 2008) is included in our analysis to check for robustness. As opposed to market power measured by price cost margins, the Boone index measures the intensity of competition in a market reflecting the degree of competitive pressure relation in the industry; a more relaxed environment will lead to a lower pressure to maximise efficiency. This refers to the "quiet life" as discussed in Berger and Hannan (1997), and more recently in Delis and Tsionas (2009). We study the impact of each of the two indices on both types of firms.

Firm performance is also determined by several other different factors such as capital expenditure, revenue growth, economic activity and financial depth among others and we use these as control variables in our empirical specification in the next section.

3. Empirical Specification

We test the implication of a changing bank market structure on the performance of financial technology firms using firm-level data from 24 industrialized countries and for comparison purposes, we also look at non-fintech firms, from the same 24 industrialized countries. Our model is a panel with firm fixed effects:[1]

$$ROA_{it} = a_i + \beta_1 ROA_{it-1} + \beta_2 CapExp_{\,it-1} + \beta_3 RevGrowth_{\,it-1} + \gamma(\Delta LI_{jt}) + \varepsilon_{it}\,, \qquad (1a)$$

$$ROA_{lt} = a_i + \beta_1 ROA_{lt-1} + \beta_2 CapExp_{\,lt-1} + \beta_3 RevGrowth_{\,lt-1} + \gamma(\Delta LI_{jt}) + \varepsilon_{it}\,, \qquad (1b)$$

i=1,2,..., 231 fintech firms, *l=1,2….,231,* non-fintech firms, *t=1,2, ..., 10* , *j=1,2,..,24* and *Δ* is the difference operator. Return on Assets (ROA) is a proxy for corporate performance and indicates how profitable a firm is in relation to its total assets (King and Santor, 2008). ROA is calculated using Trailing 12 Month Net Income over Average Total Assets. The extant literature on firm performance documents that managers change their strategies (Rajagopalan and Spreitzer, 1997) and manage earnings (Burgstahler and Eames, 2006; Dechow, 1994) in response to past performance. Making use of past performance comparisons can offer further insights into the evolution of a firm and its efficiency. Literature on firm performance includes a lagged performance variable as an explanatory variable of current performance and documents that performance tends to be positively autocorrelated (see, for instance, Garcia-Castro et al. 2010; Huang et al., 2015, among others).

Capital expenditure ratio ($CapExp$) is the Cash from operations over capital expenditures and includes the funds used by a firm to acquire, upgrade, and maintain the physical assets. Firms invest significant amounts of money on capital expenditure to support the increase in financial performance and retain the competitive advantage within the market. Some studies find a positive relationship between firm performance and capital expenditure (Jiang et al., 2006), while others suggest a negative relationship (Cooper et al., 2008).

Revenue growth (*RevGrowth*) is influenced by both internal and external factors, and it positively affects profitability (Asimakopoulos et al., 2009) and firm performance (Capon et

[1] For further details on estimating panel data models please refer to Petersen (2009), and Wooldridge (2002).

al., 1990). Firm size can be measured using sales growth; hence, we predict that sales growth will have a positive impact on firm performance. Revenue growth ($RevGrowth$) is measured as revenue growth from the current period minus revenue growth from the previous period over revenue growth of the previous period.

The market power indicator that we use is the Lerner index (LI) for the banking sector of each of the twenty-four countries – a measure of pricing above marginal cost (Global Financial Development Database (based on Bankscope, Bureau van Dijk (BvD)). Market power may be related to profits resulting from a lack of competition and the ability to raise prices above marginal cost as reflected in the LI index. Alternatively, higher concentration and profits may both be the result of an increase in competition (van Leuvensteijn et al., 2007). Consequently, we use as an alternative to the LI the Boone index (Boone, 2008), as a test for the intensity of competition (see section 6.1).

Here we are talking about the performance of the fintech industry as affected by the market power of the banking industry. Such a relationship can be either positive or negative as banks and fintechs can be viewed as selling either complementary or substitute services. We argue that increasing market power (decreasing competition) in the banking sector has a positive impact on the performance of fintech firms suggesting that the two are complementary services. Hence, the research question translates in the model used (Eq.1a) as γ being positive, or the two services are complements.

Economic activity, as measured by GDP per capita, is expected to have a positive impact on ROA, as improvements in economic activity flow through to sales activity (i.e. asset turnover ratio) and thus positively affect ROA, since asset turnover is a component of ROA (see McNamara and Duncan, 1995; Vieira et al. 2019).[2] We expect that economic activity will

[2] However, Issah and Antwi (2017) find that economic activity as measured by real GDP has a negative impact on ROA.

have a positive impact on both fintech and non-fintech firms, and hence include this as a variable to check for the robustness of our results

Improving financial depth means that the conditions for firms to improve their operating capacity and profitability are favourable (see King and Levine, 1993; Levine, 2005). Indeed, the impact of financial depth on corporate performance, reported in the literature is positive (see King and Levine, 1993; Guiso et al., 2004; and Fafchamps and Schündeln, 2013). Financial depth is measured using the size of the banking system compared to the economy (see Bencivenga and Smith, 1992; Greenwood and Jovanovic, 1990). We check for robustness using two alternative measures of financial depth, private credit by deposit money banks as a percentage of GDP (see Ashraf, 2017) and liquid liabilities as a percentage of GDP (see Owen and Pereira, 2018).

There are concerns about comparing the performance of firms from different sectors, due to the way in which certain sectors react to certain macroeconomic or market conditions (Richard et al., 2009). For this reason, we control for the industry the firm operates using industry dummies. Table 1 (Panel C) summarises the expected literature signs of the explanatory variables used in this study.

4. Sample and Summary Statistics

The fintech firms sample includes firms that have been reported in a number of fintech publications, are defined as fintech, have established subsidiaries that operate as fintech, have acquired or entered into partnership agreements with fintech firms, provide fintech services, and finally firms which invest in fintech. The list of the fintech firms and details of how these firms meet the selection criteria are provided in an online Appendix 1.

We have selected data for 231 fintech and 231 non-fintech firms. The sample period for this study is 2008 to 2017 with yearly observations. The firms have been chosen from six industries across twenty-four developed countries. Table 1 offers the number of firms classified as fintech and non-fintech, by country (Panel A) and industry (Panel B) to that they belong, while panel C, offers the expected literature signs.

[Insert Table 1]

The data for Return on Assets (ROA), Capital expenditure ratio ($CapExp$) and Revenue growth ($RevGrowth$) are collected from Bloomberg, the data for Financial depth, GDP per capita, the Lerner index and the Boone index are from the World Bank's Global Financial Development and World Development Indicators datasets, and they are derived from Bankscope. As mentioned in the introduction, the firms have been classified into one of the six industries, using the Global Industry Classification Standard (GICS) developed by MSCI and Standard and Poor's (SandP). Firm data for ROA and Capital Expenditure Ratio has been obtained from Bloomberg. Macroeconomic data collected for this study include Gross domestic product (GDP) Current (USD), GDP Annual Growth, GDP Per Capita Current (USD) and GDP Per Capita Annual Growth, this data has been collected from The World Bank Data for the period 2008 to 2017. We have applied a 1% winsorization to firm data; this limits observations below the 1st percentile and above the 99th percentile. The observations have been replaced with the mean value of all the observations that fall between the 1st and 99th percentile. From this point on the data sample referred to is the data after winsorization has been applied. [3]

5. Empirical Results

We start our analysis by comparing the sample of 231 fintech firms with the sample of 231 non-fintech firms across twenty-four industrialized countries over the period 2008 to 2017. Following Petersen (2009), we calculated robust cluster standard errors. Robust to

[3]The summary statistics are presented in the online Appendix 2.

heteroscedasticity.[4] We clustered by firm, by country and by firm and country as well. The estimates are OLS coefficients. The specifications in panel B include time (year) dummies; while the specifications in panel A do not include time (year) dummies. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated. Table 2 offers the results for the fintech sample when we include only firm-specific characteristics and as a measure of changing market power the difference in the Lerner index, ΔLI.

[Insert Table 2]

The results show that the coefficient on ΔLI is significantly positive, across all eight specifications and it is 0.3324 in the specifications without time dummies and 0.4334 in the specifications with time dummies. Table 3 offers the results for the non-fintech sample.

[Insert Table 3]

The coefficient on ΔLI is insignificant, across all the eight specifications for the non-fintech sample. The results in Tables 2 and 3 are both interesting and striking. They imply that changes in market power in the banking sector do not affect the traditional non-fintech firms (possibly because any such benefits from banking consolidation have been exhausted in this mature sector long before the period studied).[5] On the other hand, the fintech firms as a more recent sector share a symbiotic relationship complementing rather than competing with banks.

Table 4 offers the results for the fintech sample when we include firm-specific characteristics and two alternative measures of financial depth (Private credit by deposit money banks as a percentage of GDP and Liquid liabilities as a percentage of GDP), GDP per capita and five industry dummies. The coefficient on ΔLI remains significantly positive, across all

4 As Petersen writes “clustering standard errors by both firm and time appears unnecessary. In the asset-pricing example, these standard errors are identical to the standard errors clustered by time since there is no firm effect. In the corporate finance example, they are identical to the standard errors clustered by firm, since the time effect is small.”

5 Note that of the 231 non-fintech companies, 15 are banks, according to the MSCI classification.

eight specifications and ranges from 0.3764 to 0.4292, quite close to the previous estimations where we have controlled only for firm-specific characteristics.

[Insert Table 4]

6. Robustness checks

We next conduct a number of robustness checks. We start by excluding one country at a time and one industry at a time from the sample, then we use a different measure of market competition the Boone index (Boone, 2008), we use an alternative specification well known as a distributed lag model, then we account for potential non-linear relationships.

Finally, we account for the fact that the dependent variable enters the relationship in a dynamic manner. Unlike static panel data models, dynamic panel data models include lagged levels of the dependent variable as explanatory variables, violating the strict exogeneity assumption, since the lagged dependent variable is likely to be correlated with the error term (Bhargava and Sargan, 1983).

Table 5, panel A, offers the results when we exclude one country at a time from the sample, and panel B offers the results when we exclude one industry at a time from the sample. The results are not sensitive to the inclusion of any specific country or industry.

[Insert Table 5]

6.1 The Boone Index

The idea behind the indicator is that higher profits are attained by more-efficient banks, as in the DEH approach discussed in Section 2. Hence, the more negative the Boone indicator, the higher the degree of competition is because the effect of reallocation is stronger (see Hay and Liu, 1997; Boone, 2001; Griffith et al., 2005; van Leuvensteijn et. al, 2007; Boone, 2008). Therefore, a decreasing Boone index signifies a higher degree of competition resulting in more consolidation as more existing large efficient banks gain market share from inefficient banks, while an increasing Lerner index signifies a higher degree of market power. We avoid the use of more conventional measures of concentration such as the Hirschman-Herfindahl Index (HHI) as the latter looks at measuring concentration, which is not necessarily the result of market power; it may originate from more intense bank competition leading to the transfer of market share from less to more efficient institutions (who are already large, to begin with). Hence, an increase in the HHI may reflect an increase in efficiency. On the other hand, a weakness of the Boone index is that the efficiency gains will not necessarily translate into lower prices in an environment of high concentration. We expect that the sign of the coefficient on *Δ* Boone will be negative, indicating that a lowering of competition in the banking sector will increase the RoA of fintech firms. Table 6 offers the results for the fintech sample when we use as a measure of changing market power the difference of the Boone index, *Δ*Boone.

[Insert Table 6]

The results are consistent with the results when as a measure of market power we use the Lerner index. Since the coefficients are negative, across all the eight specifications, as expected, and it is equal to -0.0665 for the specifications without time dummies and -0.0585 in the specifications with time dummies, however, it is significant only in the specifications where we use the White standard and standard errors clustered by firm only.

6.2 A Distributed lag model

In this section, we test whether the distributed lag model is more relevant. The model described by Eq. (1b) is equivalent to an order one distributed lag model:

$$ROA_{it} = a_i + \beta_1 ROA_{it-1} + \beta_2 CapExp_{\,it-1} + \beta_3 RevGrowth_{\,it-1} + \beta_4 LI_{it} + \beta_5 LI_{it-1} + \varepsilon_{it} \quad (2)$$

under the linear equality constraint: H_0: $\beta_4 = -\beta_5$, H_A: $\beta_4 \neq -\beta_5$, which can be tested using a Wald test. The results are presented in Table 7.

[Insert Table 7]

The F-statistic in general is insignificant, which means we cannot reject the hypothesis that the two effects are of equal magnitude and opposite signs. The only exceptions are when we cluster by country and by country and firm and we include time dummies, specifications seven and eight. In these specifications, the F-statistic is significant, which means we can reject the hypothesis that the two effects have equal magnitude and opposite signs. However, all the β_4 coefficients enter the relations in a statistically positive and significant manner, while all the β_5 coefficients enter the relations in a statistically negative and significant manner.[6] For instance, β_4 is equal to 0.4051 and β_5 is equal to -0.4942 and they are both significant at 1% level of significance in both specifications (7) and (8).

Hence, it makes more sense to use the model with the first differences instead of an order one distributed lag model. Moreover, with distributed lag models there is the problem that successive lags tend to have high correlations (multicollinearity), leading to smaller t-ratios and incorrect inferences.

6.3 Potential nonlinear relationships

In this section, we explore whether there is a potential non-linear relationship between the change in bank market power (as measured using the Lerner index) and the performance of the fintech companies (as measured using ROA). The quadratic term of the change in market power (ΔLI^2) is included in the basic model Eq. (1b).

$$ROA_{it} = a_i + \beta_1 ROA_{it-1} + \beta_2 CapExp_{\,it-1} + \beta_3 RevGrowth_{\,it-1} + \gamma(\Delta LI_{it}) + \delta(\Delta LI_{it}^2) + u_{it} \quad (3)$$

Table 8 presents the results. The coefficients of both ΔLI and ΔLI^2 turn insignificant in all the specifications except for the cases where we cluster for country effects, namely specifications (3), (4), (7) and (8). In these specifications, the quadratic term has a positive sign, the linear term a negative sign and the constant term again a positive sign, which directs to a convex U-shaped relationship between fintech performance and changing market power. The turning points of ΔLI are also computed in Table 8.

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[6] The results are available upon request.

[Insert Table 8]

6.4 Accounting for Endogeneity

In this section, we study the possible endogeneity of the explanatory variables. There is no reverse causality between ΔLI and performance of fintech companies.

However, since we have included the lagged dependent variable in the model, the model is dynamic. The predicted sign of the lagged dependent variable is positive. The panel ordinary least squares (POLS) estimator is upward biased (when the error term is positively autocorrelated). To address this concern the generalized method of moments is used. More specifically, Table 9 examines the performance of the model under two estimation procedures, namely the System Generalized Method of Moments (GMM) estimator of Blundell and Bond, (1998) in columns (1) and (3) and the difference GMM method of Arellano and Bond (1991) in columns (2) and (4). The System GMM estimator stacks together the first differenced equation and the level equation in a system of equations. The panel GMM estimator has several advantages. It utilizes the time-series variation in the data, considers any unobserved cross-section-specific effects, permits the inclusion of lagged dependent variables as explanatory variables, and controls for the endogeneity of all the independent variables, by using internal instruments (previous realizations of the explanatory variables).

[Insert Table 9]

The Capital expenditure ratio was treated as a predetermined or sequentially exogenous variable that is the model is estimated under the assumption that ε_{it} can be correlated with future regressors but it remains orthogonal to contemporaneous regressors. Hence, valid instruments are first and deeper lags of the instrumenting variable for the differenced equation and, for the system GMM, the zero lag of the instrumenting variable in differences for the levels equation. The lagged return on assets (ROA), Revenue growth and the difference in the Lerner index were treated as endogenous variables that is the estimation is under the assumption that ε_{it} can be correlated with future and contemporaneous regressors but ε_{it} remains orthogonal to past regressors. In this case, valid instruments are second and deeper lags of the instrumenting variable for the differenced equation and, for the System GMM, the first lag of the instrumenting variable in differences for the levels equation. Table 9 shows that the results remain valid under GMM estimation.

7. Conclusions

We find that changes in market power in the banking sector do not affect the performance of firms in the traditional financial sector, which includes banks too. On the one hand, this implies that any benefits from banking consolidation on the performance of non-fintech firms have long been exhausted in this mature sector. On the other hand, the impact of changes in the banking Lerner index on the performance of fintech firms is positive and statistically significant, thus establishing that the latter share a complementary rather than a competing relationship with banks.

The direct relationship of the impact of changes in bank market power on the performance of fintech firms remains valid in a series of robustness tests. This includes the replacement of the Lerner index with the Boone index as an explanatory variable. This replacement allows for changes in the performance of firms stemming from changes in bank concentration, the latter reflecting changes in efficiency rather than the market power of banks. The relationship is also robust to tests for additional control variables, excluding one country at a time and one industry at a time from the sample, alternative specifications, such as a distributed lag model, and nonlinearity and endogeneity.

The results in our paper are novel and provide an important first insight into the current mode of competition between fintechs and banks. This is important and of topical interest, establishing a launching step for further research on the future evolution of the relationship between traditional finance and the fintech sector.

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Tables

Table 1. Number of firms by country and industry and expected literature signs.

Panel A. Number of firms by country.

Country	fintech	non-fintech	Total
Australia	28	28	56
Austria	2	2	4
Belgium	2	2	4
Canada	19	19	38
Denmark	3	3	6
Finland	4	4	8
France	18	18	36
Germany	4	4	8
HK	6	6	12
Ireland	2	2	4
Israel	7	7	14
Italy	9	9	18
Japan	12	12	24
Netherlands	1	1	2
New Zealand	5	5	10
Norway	4	4	8
Portugal	1	1	2
Singapore	6	6	12
South Korea	14	14	28
Spain	3	3	6
Sweden	13	13	26
Switzerland	4	4	8
UK	8	8	16
US	56	56	112
Total	**231**	**231**	**462**

Panel B. Number of firms by industry.

Classification	fintech	non-fintech	Total
Professional Services (202020)	8	24	32
Banks (401010)	29	15	44
Consumer Finance (402020)	22	19	41
Capital Markets (402030)	57	82	139
IT Services (451020)	68	45	113
Software (451030)	47	46	93
Total	**231**	**231**	**462**

Panel C. Dependent Variable: ROA	
Variable	**Expected (literature) sign**
Lagged ROA	Positive
$CapExp$	Positive/ Negative
$RevGrowth$	Positive
	Independent variables
ΔLI	Positive
ΔBoone	Negative
Private credit/GDP	Positive
Liquid liabilities to GDP	Positive
GDP per capita	Positive

Notes: The data are from Bloomberg and the firms have been classified to one of the six industries using the Global Industry Classification Standard (GICS) developed by MSCI and Standard and Poor's (SandP).

Table 2. Panel ordinary least squares estimation (POLS). Developed markets fintech companies. Lerner

Dependent variable Return on Assets (ROA)				
Panel A				
	(1)	(2)	(3)	(4)
LROA	0.6918***	0.6918***	0.6918***	0.6918***
	(0.0799)	(0.0835)	(0.0282)	(0.0282)
$LCapExp$	0.0000	0.0000**	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LRevGrowth$	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔLI	0.3324***	0.3324***	0.3324**	0.3324**
	(0.1279)	(0.1292)	(0.1306)	(0.1306)
_cons	0.0090	0.0090	0.0090	0.0090
	(0.0068)	(0.0068)	(0.0084)	(0.0084)
R2	64.75%	64.75%	64.75%	64.75%
Observations	682	682	682	682
Panel B				
	(5)	(6)	(7)	(8)
LROA	0.6921***	0.6921***	0.6921***	0.6921***
	(0.0797)	(0.0839)	(0.0273)	(0.0273)
$LCapExp$	0.0000	0.0000**	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LRevGrowth$	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔLI	0.4334***	0.4334***	0.4334***	0.4334***
	(0.1444)	(0.1523)	(0.1148)	(0.1148)
_cons	-0.0016	-0.0016	-0.0016	-0.0016
	(0.0125)	(0.0133)	(0.0163)	(0.0163)
R2	65.11%	65.11%	65.11%	65.11%
Observations	682	682	682	682
Standard errors	White	CL −F	CL −C	CL −FandC

Notes. The independent variables are defined in the text. The estimates in columns I–IV are OLS coefficients. The specifications in panel B include time (year) dummies. Standard errors are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. White standard errors are reported in column I, standard errors clustered by firm in column II (CL −F), by country in column III (CL −C), and by firm and country in column IV (CL −FandC). POLS, panel ordinary least squares estimation. *L.* stands for the first lag and Δ stand for the first difference of the variable, namely $X_t - LX_t$. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Table 3: Panel ordinary least squares estimation (POLS). Developed markets non-fintech companies. Lerner

Dependent variable Return on Assets (ROA)				
Panel A.				
	(1)	(2)	(3)	(4)
LROA	0.5225***	0.5225***	0.5225***	0.5225***
	(0.0776)	(0.0761)	(0.0567)	(0.0567)
$LCapExp$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LRevGrowth$	0.0020	0.0020	0.0020	0.0020
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
ΔLI	-0.1720	-0.1720	-0.1720*	-0.1720*
	(0.1282)	(0.1212)	(0.0916)	(0.0916)
_cons	0.0057	0.0057	0.0057	0.0057
	(0.0076)	(0.0071)	(0.0060)	(0.0060)
R2	40.88%	40.88%	40.88%	40.88%
Observations	769	769	769	769
Panel B.				
	(5)	(6)	(7)	(8)
LROA	0.5221***	0.5221***	0.5221***	0.5221***
	(0.0768)	(0.0750)	(0.0566)	(0.0566)
$LCapExp$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LRevGrowth$	0.0022	0.0022	0.0022	0.0022
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
ΔLI	-0.0672	-0.0672	-0.0672	-0.0672
	(0.1234)	(0.1230)	(0.1017)	(0.1017)
_cons	0.0075	0.0075	0.0075	0.0075
	(0.0178)	(0.0176)	(0.0143)	(0.0143)
R2	41.40%	41.40%	41.40%	41.40%
Observations	769	769	769	769
Standard errors	White	CL −F	CL −C	CL −FandC

Notes. The independent variables are defined in the text. The estimates in columns I–IV are OLS coefficients. The specifications in panel B include time (year) dummies. Standard errors are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. White standard errors are reported in column I, standard errors clustered by firm in column II (CL −F), by country in column III (CL −C), and by firm and country in column IV (CL −FandC). POLS, panel ordinary least squares estimation. *L*. stands for the first lag and Δ stands for the first difference of the variable, namely $X_t - LX_t$. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Table 4: Panel ordinary least squares estimation (POLS). Developed markets fintech companies. Lerner

Dependent variable Return on Assets (ROA)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LROA	0.7008***	0.7079***	0.6920***	0.7074***	0.7074***	0.6844***	0.7028***	0.7020***
	(0.0572)	(0.0570)	(0.0570)	(0.0577)	(0.0574)	(0.0313)	(0.0603)	(0.0603)
$LCapExp$	0.0000***	0.0000***	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LRevGrowth$	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔLI	0.3869***	0.3881***	0.4292***	0.3803***	0.3821***	0.4214***	0.3826***	0.3764***
	(0.1197)	(0.1210)	(0.1210)	(0.1210)	(0.1225)	(0.1084)	(0.1261)	(0.1246)
Private credit/GDP.	0.0000			0.0000			0.0000	
	(0.0000)			(0.0000)			(0.0000)	
Liquid liabilities to GDP		0.0000			0.0000			0.0000
		(0.0000)			(0.0000)			(0.0000)
D1						-0.0150	-0.0225	-0.0219
						(0.0183)	(0.0176)	(0.0175)
D2						-0.0073	-0.0108*	-0.0111*
						(0.0079)	(0.0062)	(0.0065)
D3						-0.0257	-0.0262	-0.0260
						(0.0209)	(0.0252)	(0.0256)
D4						-0.0276***	-0.0289***	-0.0277***
						(0.0066)	(0.0077)	(0.0058)
D5						-0.0815	-0.0158*	-0.0155*
						(0.0740)	(0.0087)	(0.0091)
GDP per capita			0.0000	0.0000	0.0000		0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
_cons	0.0169	0.0158	-0.0111	0.0027	0.0027	0.0015	0.0046	0.0140
	(0.0121)	(0.0124)	(0.0183)	(0.0130)	(0.0130)	(0.0129)	(0.0097)	(0.0113)
R2	66.47%	66.47%	65.12%	66.49%	66.49%	65.65%	66.78%	66.78%
Observations	650	650	682	650	650	682	650	650
Standard errors	CL −FandC	CL −FandC	CL −FandC	CL −FandC	CL −FandC	CL −FandC	CL −FandC	CL −FandC

Notes. The independent variables are defined in the text. The estimates in columns I–IV are OLS coefficients. The specifications include time (year) dummies. Standard errors are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. Standard errors clustered by firm and country (CL −FandC). POLS, panel ordinary least squares estimation. L. stands for the first lag and Δ stands for the first difference of the variable, namely $X_t - LX_t$. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated. D1 is a dummy variable that takes the value of 1 if the company belongs to Software (451030) and zero otherwise. D2 is a dummy variable that takes the value of 1 if the company belongs to IT Services (451020) and zero otherwise. D3 is a dummy variable that takes the value of 1 if the company belongs to Professional Services (202020) and zero otherwise. D4 is a dummy variable that takes the value of 1 if the company belongs to Banks (401010) and zero otherwise. D5 is a dummy variable that takes the value of 1 if the company belongs to Consumer Finance (402020) and zero otherwise. The reference group was the companies that belong to Capital Markets (402030). Firms have been filtered using the MSCI classification codes for each of the six industries.

Table 5: Robustness Checks.

Dependent variable Return on Assets (ROA)								
Panel A.								
Country	LROA	$LCapExp$	$LRevGrowth$	ΔLI	_cons	R2	N	Standard errors
Australia	0.6828***	0.0000*	-0.0011	0.4344***	-0.0219	64.58%	663	CL −FandC
	(0.0337)	(0.0000)	(0.0010)	(0.1168)	(0.0133)			
Austria	0.6921***	0.0000**	0.0001***	0.4334***	-0.0016	65.11%	681	CL −FandC
	(0.0274)	(0.0000)	(0.0000)	(0.1150)	(0.0163)			
Belgium	0.6921***	0.0000**	0.0001***	0.4363***	-0.0020	65.12%	670	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1159)	(0.0167)			
Canada	0.7073***	0.0000***	0.0001***	0.3925***	0.0129***	66.59%	652	CL −FandC
	(0.0567)	(0.0000)	(0.0000)	(0.1198)	(0.0057)			
Denmark	0.6904***	0.0000**	0.0001***	0.4488***	0.0298***	64.90%	664	CL −FandC
	(0.0275)	(0.0000)	(0.0000)	(0.1184)	(0.0101)			
Finland	0.6922***	0.0000**	0.0001***	0.4342***	-0.0016	65.10%	681	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1150)	(0.0163)			
France	0.6931***	0.0000**	0.0001***	0.4755***	0.0291***	65.27%	607	CL −FandC
	(0.0277)	(0.0000)	(0.0000)	(0.1296)	(0.0111)			
Germany	0.6920***	0.0000**	0.0001***	0.4346***	-0.0015	65.09%	676	CL −FandC
	(0.0277)	(0.0000)	(0.0000)	(0.1156)	(0.0165)			
HK	0.6875***	0.0000	0.0001***	0.4177***	0.0226	66.32%	665	CL −FandC
	(0.0378)	(0.0000)	(0.0000)	(0.1171)	(0.0159)			
Ireland	0.6920***	0.0000**	0.0001***	0.4355***	0.0294***	65.11%	678	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1165)	(0.0099)			
Israel	0.6917***	0.0000**	0.0001***	0.4168***	0.0007	65.47%	642	CL −FandC
	(0.0276)	(0.0000)	(0.0000)	(0.1189)	(0.0168)			
Italy	0.6954***	0.0000**	0.0001***	0.4395***	0.0329***	65.92%	651	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1216)	(0.0096)			
Japan	0.6938***	0.0000*	0.0001***	0.4476***	-0.0008	65.54%	627	CL −FandC
	(0.0275)	(0.0000)	(0.0000)	(0.1292)	(0.0179)			
Netherlands	0.6921***	0.0000**	0.0001***	0.4334***	-0.0016	65.11%	682	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1148)	(0.0163)			
New Zealand	0.6917***	0.0000**	0.0001***	0.4347***	-0.0016	64.84%	677	CL −FandC
	(0.0278)	(0.0000)	(0.0000)	(0.1151)	(0.0163)			
Norway	0.6921***	0.0000**	0.0001***	0.4342***	-0.0015	65.12%	676	CL −FandC
	(0.0278)	(0.0000)	(0.0000)	(0.1150)	(0.0164)			
Portugal	0.6921***	0.0000**	0.0001***	0.4334***	-0.0016	65.11%	682	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1150)	(0.0163)			
Singapore	0.6667***	0.0000*	0.0001***	0.3959***	-0.0033	62.57%	657	CL −FandC
	(0.0192)	(0.0000)	(0.0000)	(0.1157)	(0.0179)			
South Korea	0.6922***	0.0000**	0.0001***	0.4387***	-0.0016	65.14%	673	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1155)	(0.0163)			
Spain	0.6923***	0.0000**	0.0001***	0.4603***	0.0314***	65.17%	664	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1197)	(0.0098)			
Sweden	0.6957***	0.0000*	0.0001***	0.4435***	-0.0021	65.26%	657	CL −FandC
	(0.0277)	(0.0000)	(0.0000)	(0.1165)	(0.0169)			
Switzerland	0.6926***	0.0000**	0.0001***	0.4979***	-0.0046	65.23%	670	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1070)	(0.0168)			
UK	0.6986***	0.0000**	0.0001***	0.3541***	0.0302***	66.37%	658	CL −FandC
	(0.0273)	(0.0000)	(0.0000)	(0.1060)	(0.0101)			
US	0.6833***	0.0000**	0.0001***	0.4195***	-0.0102	63.04%	433	CL −FandC
	(0.0330)	(0.0000)	(0.0000)	(0.1155)	(0.0259)			

Table 5 continued. Robustness Checks.

Panel B.								
Industry	LROA	$LCapExp$	$LRevGrowth$	ΔLI	_cons	R2	N	Standard errors
202020	0.6904***	0.0000**	0.0001***	0.4313***	0.0284***	65.14%	651	CL −FandC
	(0.0275)	(0.0000)	(0.0000)	(0.1366)	(0.0100)			
401010	0.6892***	0.0000	0.0001***	0.5290***	-0.0238*	65.88%	558	CL −FandC
	(0.0349)	(0.0000)	(0.0000)	(0.1405)	(0.0139)			
402020	0.6254***	0.0000**	0.0001***	0.3900***	0.0379***	66.38%	639	CL −FandC
	(0.0675)	(0.0000)	(0.0000)	(0.1159)	(0.0107)			
402030	0.6872***	0.0000*	-0.0007	0.4318***	0.0312***	65.95%	513	CL −FandC
	(0.0336)	(0.0000)	(0.0012)	(0.1551)	(0.0122)			
451020	0.7621***	0.0000***	0.0002***	0.4516***	-0.0082***	68.69%	482	CL −FandC
	(0.0336)	(0.0000)	(0.0000)	(0.1456)	(0.0154)			
451030	0.6936 ***	0.0000*	0.0001***	0.3653***	-0.0008***	59.43%	567	CL −FandC
	(0.0403)	(0.0000)	(0.0000)	(0.1068)	(0.0143)			

Notes. The industries are defined in Table1 (Panel B). The independent variables are defined in the text. The estimates are OLS coefficients. In Panel A in the first column is the country excluded each time from the sample. In Panel B in the first column is the industry excluded each time from the sample. The specifications include time (year) dummies. Standard errors are reported in parentheses. Standard errors clustered by firm and country (CL −FandC). ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. POLS, panel ordinary least squares estimation. L. stands for the first lag, Δ stands for the first difference of the variable, namely $X_t - LX_t$ and N for the number of observations. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Table 6: Panel ordinary least squares estimation (POLS). Developed markets fintech companies. Boone

Dependent variable Return on Assets (ROA)				
Panel A				
	(1)	(2)	(3)	(4)
LROA	0.6956***	0.6956***	0.6956***	0.6956***
	(0.0771)	(0.0801)	(0.0298)	(0.0298)
$LCapExp$	0.0000	0.0000**	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	0.0001***	0.0001***	0.0001***	0.0001***
$LRevGrowth$)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	-0.0665**	-0.0665*	-0.0665	-0.0665
ΔBoone	(0.0307)	(0.0352)	(0.0539)	(0.0539)
	0.0013**	0.0013**	0.0013*	0.0013*
_cons	(0.0051)	(0.0056)	(0.0070)	(0.0070)
R2	64.47%	64.47%	64.47%	64.47%
Observations	742	742	742	742
Panel B				
	(5)	(6)	(7)	(8)
LROA	0.6963***	0.6963***	0.6963***	0.6963***
	(0.0772)	(0.0780)	(0.0293)	(0.0293)
$LCapExp$	0.0000	0.0000**	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	0.0001***	0.0001***	0.0001***	0.0001***
$LRevGrowth$	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	-0.0585*	-0.0585	-0.0585	-0.0585
ΔBoone	(0.0340)	(0.0388)	(0.0465)	(0.0465)
	0.0016	0.0016	0.0016	0.0016
_cons	(0.0117)	(0.0120)	(0.0147)	(0.0147)
R2	64.64%	64.64%	64.64%	64.64%
Observations	742	742	742	742
Standard errors	White	CL −F	CL −C	CL −FandC

Notes. The independent variables are defined in the text. The estimates in columns I–IV are OLS coefficients. The specifications in panel B include time (year) dummies. Standard errors are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. White standard errors are reported in column I, standard errors clustered by firm in column II (CL −F), by country in column III (CL −C), and by firm and country in column IV (CL −FandC). POLS, panel ordinary least squares estimation. *L*. stands for the first lag and Δ stands for the first difference of the variable, namely $X_t - LX_t$. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Table 7. Testing an order one distributed lag model.

Testing for equality constraints: H0: $\beta_4 = -\beta_5$ HA: $\beta_4 \neq -\beta_5$. Wald test.				
Panel A	(1)	(2)	(3)	(4)
F-statistic	1.71	1.25	2.63	2.63
Prob > F	19.13%	26.50%	11.95%	10.68%
Panel B.	(5)	(6)	(7)	(8)
F-statistic	2.51	1.73	4.63	4.63
Prob > F	11.35%	19.02%	4.31%	3.30%
Standard errors	White	CL −F	CL −C	CL −FandC

Notes. The estimates in columns I–IV are OLS coefficients. The specifications in panel B include time (year) dummies. Standard errors are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. White standard errors are reported in column I, standard errors clustered by firm in column II (CL −F), by country in column III (CL −C), and by firm and country in column IV (CL −FandC). POLS, panel ordinary least squares estimation.

Table 8. **Accounting for Nonlinearity**

Dependent variable Return on Assets (ROA)				
Panel A.				
	(1)	(2)	(3)	(4)
LROA	0.5226***	0.5226***	0.5226***	0.5226***
	(0.0777)	(0.0763)	(0.0568)	(0.0568)
$LCapExp$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	0.00197	0.00197	0.00197	0.00197
$LRevGrowth$	(0.0021)	(0.0020)	(0.0020)	(0.0020)
	-0.2603*	-0.2603	-0.2603***	-0.2603***
ΔLI	(0.1467)	(0.1609)	(0.0867)	(0.0867)
	1.1961	1.1961	1.1961**	1.1961**
ΔLI^2	(0.9866)	(1.0351)	(0.5019)	(0.5019)
	0.0033	0.0033	0.0033	0.0033
_cons	(0.0084)	(0.0075)	(0.0064)	(0.0064)
R2	40.94%	40.94%	40.94%	40.94%
Observations	769	769	769	769
Turning point –γ/2δ	0.1088	0.1088	0.1088	0.1088
Panel B.				
	(5)	(6)	(7)	(8)
LROA	0.5221***	0.5221***	0.5221***	0.5221***
	(0.0768)	(0.0751)	(0.0566)	(0.0566)
$LCapExp$	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LRevGrowth$	0.0022	0.0022	0.0022	0.0022
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
	-0.1953	-0.1953	-0.1953*	-0.1953*
ΔLI	(0.1467)	(0.1595)	(0.1043)	(0.1043)
	1.8891*	1.8891*	1.8891**	1.8891***
ΔLI^2	(1.0971)	(1.0847)	(0.6826)	(0.6826)
	0.0060	0.0060	0.0060	0.0060
_cons	(0.0179)	(0.0178)	(0.0145)	(0.0145)
R2	41.55%	41.55%	41.55%	41.55%
Observations	769	769	769	769
Turning point –γ/2δ	0.0517	0.0517	0.0517	0.0517
Standard errors	White	CL −F	CL −C	CL −FandC

Notes. The independent variables are defined in the text. The estimates in columns I–IV are OLS coefficients. The specifications in panel B include time (year) dummies. Standard errors are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. White standard errors are reported in column I, standard errors clustered by firm in column II (CL −F), by country in column III (CL −C), and by firm and country in column IV (CL −FandC). POLS, panel ordinary least squares estimation. *L.* stands for the first lag and Δ stand for the first difference of the variable, namely $X_t - LX_t$. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Table 9: Generalized Method of Moments estimations.

Dependent variable Return on Assets (ROA)				
Explanatory variable	SGMM-one step (1)	DGMM-one step (2)	SGMM-two step (3)	DGMM-two step (4)
LROA	0.6412***	0.3886***	0.6001***	0.3721***
	(0.0799)	(0.0845)	(0.0762)	(0.0738)
$LCapExp$	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	0.0001***	0.0000	0.0001**	0.0000
$LRevGrowth$	(0.0000)	(0.0001)	(0.0000)	(0.0001)
	0.4854***	0.4940**	0.3734**	0.4763***
ΔLI	(0.1707)	(0.1959)	(0.1539)	(0.1839)
	0.0060		0.0182	
_cons	(0.0137)		(0.0162)	
Wald chi2(31)	2101.57	1797.44	723.03	2681.27
Number of instruments	14	12	14	12
Observations	682	538	682	538

Notes. The independent variables are defined in the text. All specifications contain time (year) dummies. Robust standard errors are displayed in parentheses. *** Significance at 1%, ** significance at 5%, * significance at 10%. DGMM, difference generalised method of moments estimation as in Arellano and Bond (1991); SGMM, system generalised method of moments estimation as in Blundell and Bond (1998). The Capital expenditure ratio was treated as predetermined or sequentially exogenous variables while the lagged return on assets (ROA), Revenue growth and the difference in the Lerner index were treated as endogenous variables. The matrix of instruments is 'collapsed' (see Roodman, 2009). The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Appendix.

In this section, we make a brief discussion of the summary statistics of our sample. Table A3., offers the summary statistics for the firm characteristics of the 231 fintech firms (Panel A) and the 231 non-fintech firms (Panel B) across twenty-four countries, while panel C offers the summary statistics for the macroeconomic and bank market structure characteristics in which these companies operate. The variables are winsorized at the 1% level in both tails of the distribution, by year, before the summary statistics are calculated.

Table A3. Summary statistics.

Panel A. Fintech sample. firm characteristics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
ROA	-0.0805	0.0153	0.7410	-6.9782	0.4917	-6.2975	63.4421
$CapExp$	-6.7241	4.4613	6319.6000	-6645.1680	375.7484	-0.6774	224.2009
$RevGrowth$	0.4633	0.0782	64.9389	-0.9863	3.1693	14.4217	251.8787

Panel B. Non-fintech sample. firm characteristics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
ROA	-0.0186	0.0259	1.1078	-3.3449	0.3007	-5.1491	43.6435
$CapExp$	7.5460	4.2763	7202.5000	-3406.0630	351.9547	8.3071	218.4904
$RevGrowth$	0.3770	0.0610	40.0640	-0.9697	2.2677	11.1491	152.6062

Panel C. Macroeconomic and Bank Market structure characteristics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
ΔLI	0.0200	0.0156	0.2265	-0.1675	0.0604	0.0508	4.4466
ΔBoone	0.0058	0.0012	0.4906	-0.5908	0.0952	-0.2553	19.3896
PC/GDP	115.1607	108.8365	218.944	49.1968	38.9385	0.4842	2.6956
M3/GDP	112.8681	95.5960	368.9220	49.2393	59.4262	2.3756	9.1787
GDPpc	46470.6800	46185.1000	91451.4000	20803.5000	14831.2200	0.9681	4.3476

Notes: There are 231 fintech firms and 231 non-fintech firms from 24 industrialised countries and the period under study is 2008-2017. PC/GDP stands for Private credit by deposit money banks as a percentage of GDP, M3/GDP stands for Liquid liabilities as a percentage of GDP and GDPpc stands for GDP per capita. The variables are winsorized at the 1% level in both tails of the distribution before the summary statistics are calculated.

Starting with the fintech sample, the ROA ranges from -6.9782 (iSignthis Ltd, 2015) to 0.7410 (Silverlake Axis Ltd, 2017) with a mean of -0.0805. ROA and Capital expenditure ratio are negatively skewed, while the revenue growth is positively skewed.

Moving to the non-fintech sample, the ROA ranges between -3.3449 (Jaxsta Ltd, 2010) and 1.1078 (Minco Capital Corp, 2015) with a mean of -0.0186. Capital expenditure ratio and revenue growth are positively skewed, while ROA is negatively skewed. All the variables for both the fintech and the non-fintech sample have a kurtosis of more than 3 indicating leptokurtic distribution. The standard deviations for ROA, revenue growth, and capital expenditure ratio are above the mean values and hence they are highly volatile for both samples as well.

The change in the Lerner index across the twenty-four countries ranges from -0.1675 (Switzerland, 2012) to (Canada, 2010) with a mean of 0.0200. The GDP per capita across the twenty-four countries ranges from 20,803 (South Korea, 2008) to 91,451 (Norway, 2017) with a mean of 46470. All the macroeconomic and bank market structure characteristics are leptokurtic except for Liquid liabilities, and they are all positively skewed, except for the Boone index. The change in Lerner and Boone indexes are highly volatile while the other macroeconomic and bank market structure characteristics have low volatility.