Digital disruption and market structure: the case of internet banking

Bruce Lyons* and Minyan Zhu**

* School of Economics and Centre for Competition Policy, University of East Anglia, Norwich, NR4 7TJ, UK

Email: b.lyons@uea.ac.uk

**Department of Economics, University of Reading, Reading, RG6 6EL, UK

Email: minyan.zhu@reading.ac.uk

Abstract

We provide an econometric study of the adoption of internet banking, a case of a potentially disruptive digital technology which could devalue/replace incumbent legacy. Our aim is to better understand the extent to which it disrupted market structure where incumbents start with a strong customer base. We study both regional integration and national concentration dimensions of market structure in EU member states during the period of 1997-2018. We find that internet banking was initially introduced earlier in more concentrated markets. Although consumer uptake was then slower over time than in less concentrated markets, the initial higher consumer penetration in more concentrated markets was sustained until market maturity. We further find a substantial de-concentrating effect of internet banking, and evidence of integration in previously regionalised markets following uptake.

Keywords: Digital Disruption, Internet Banking, Endogenous Market Structure, Market Integration

JEL Codes: L11, O33, F15, G21, L81

1. Introduction

Much has been written about how digital technology is transforming the ways firms compete,[1] especially on the rise to dominance of a small number of global big tech firms who entered or created markets with internet-only products and no substantial existing customer base (such as Google, Amazon, Facebook (Meta) and Netflix). However, much less is known about how the adoption of digital technology, when promoted *alongside* traditional face-to-face customer models (e.g. financial services), disrupts market structure. Internet banking (also known as online banking or web banking) – a product for which incumbent banks introduced an internet consumer interface alongside the pre-existing face-to-face networks of bricks-and-mortar retail outlets (branches) – is a leading example of a potentially disruptive technology that can be examined empirically.

Internet banking is not limited to the original innovator or restricted by licence agreements. In contrast with the branch banking business model (which has a very expensive cost structure requiring a heavy investment in a branch network), internet banking is not geographically tied to where the customers are. More importantly, in what is becoming a much wider digital transformation of consumer banking, internet banking has the potential to replace or devalue the legacy systems of incumbents, as it allows users to access online almost all services traditionally available from a branch. In principle, this should facilitate both de novo entry and cross-entry by previously regional banks, which should be expected to lead to long-term changes in market structure. This raises questions such as the short and medium term effects of initial market structure on the introduction and consumer adoption of digital services, and the consequent direction and speed of change of endogenous market structure.

One of our aim is therefore to understand the extent to which the adoption of a digital technology (by way of its speed and extent) disrupts the structure of a market where incumbents start with a strong customer base, and to draw implications for market contestability as well as advantages/challenges faced by incumbents and entrants. By focussing on EU member states with vastly varying degrees of regionalisation across their (pre-internet) banking markets, we are further able to separate the regional integration and national concentration dimensions of market structure.

We specify our research questions more precisely in the next section, with summarised findings and our contribution to the relevant literature. Section 3 sets out our modelling approach and model specifications. Section 4 describes our data and presents some stylised facts. Section 5 explains our empirical strategy and section 6 details our estimation results. Section 7 presents robustness checks. Section 8 concludes and draws implications from our findings.

2. Research questions, related literature and our high-level empirical findings[2]

[1] See, for example, The Furman Review (2019).

[2] The literature mentioned in this section is by no means complete. Our intention is to link to the literature we think most relevant to our study and indicate to what extent we have contributed to it.

Taking account of the endogeneity of consumer uptake of internet banking and market structure, we investigate the following research questions (RQ):

RQ 1: How did market structure affect consumer acceptability and uptake of internet banking?

A delay in uptake means that potential consumer surplus is lost for that time period, and this loss is likely to be substantial for a major innovation.[3] Consumer uptake of a technology or new product/service often takes a number of years, particularly where acceptability depends, at least in part, on observing other users. This drag on diffusion increases in importance if there are network effects (e.g. mobile phones), learning effects (e.g. home computing), fear of side-effects (e.g. vaccines), or concerns over security (e.g. financial services). More specifically, trust and reputation are crucial for financial services because everyday transactions (payments), personal wealth (savings), or potentially large future claims (insurance) are at stake. These demand-side factors give incumbent providers a substantial advantage in a mature market with near-universal geographic coverage.

To empirically understand consumer acceptability and uptake of any disruptive innovation, we draw on the strand of literature relating to the speed of uptake (consumer diffusion) of new products or new service delivery methods. Building on the pioneering work of Griliches (1957), this econometric approach was first applied to a consumer product, mobile phones, by Gruber and Verboven (2001a, 2001b). Li and Lyons (2012) develop this approach to examine the role of market structure and regulation over a more-or-less complete cycle of consumer adoption. We follow a similar methodology in order to understand how market context affects consumer acceptability of internet banking, as reflected in the speed of uptake.

There has been very little econometric research on the effect of market structure on user adoption of internet banking. Takieddine and Sun (2015) consider consumer usage across 33 European countries but only as a cross-section in 2013 (so they cannot distinguish speed from timing effects which we explain Section 3.1).[4] Nickerson and Sullivan (2003) and Sullivan and Wang (2013) investigate the timing of the initial adoption of internet banking technology by US banks (i.e. by firms as opposed to by consumers) across US regions.[5]

[3] To get a very rough ballpark feel for the magnitude of this loss, consider a consumer with linear potential demand (standardised with unit slope). If q is each consumer's demand at the competitive price, delayed uptake foregoes $0.5q^2$ of potential consumer surplus per period. By comparison, market power which increases price and reduces demand by 10% would mean a per period consumer surplus loss of $[0.9*0.1 + 0.5*0.1*0.1]q^2 = 0.095q^2$. So, even without discounting, a four-year delay in uptake of the new product would be equivalent in consumer surplus terms to enduring 21 years of this level of monopoly power.

[4] They find that "the effects of socio-economic and technology-related factors on Internet banking diffusion are fully mediated by Internet access" [p.361]. This supports our later assumption that the maximum consumer uptake is determined by internet access.

[5] In terms of our consumer uptake model, their results are relevant to the timing parameter, but not to the speed parameter. They find that larger banks in more concentrated markets adopt earlier, which they explain in terms of the incentive to exercise their strategic option earlier than banks with smaller market shares. We find a similar result.

We add to this literature by providing new evidence relating to consumer uptake of internet banking. This has two stages in that firms must first introduce a new technology, then consumers must adopt it. We find that internet banking was introduced earlier in concentrated markets, possibly due to the capability of relatively large banks to convert existing customers on a large scale. However, our results also show that the speed of consumer uptake was slower in concentrated markets. This may be because incumbents most invested in an expensive bricks-and-mortar network are less aggressive in encouraging their customers to take up internet banking, at least beyond those they were most likely to lose if they had not innovated early.

RQ2: What effect has the uptake of internet banking had on the evolution of national market concentration?

Disruptive innovation is seen to be a core part of firms' strategic management that could change industry structure (Christensen, 1997). Using data on the hard disk industry, Christensen and Rosenbloom (1995) illustrate that incumbents are usually successful in defending their position by addressing customers' needs within the value network in which the incumbents competed, but an entrant can change the context within which a firm competes (emerging value networks) and solve some customer problems. Therefore, 'disruption' occurs when incumbents focus on existing customers and/or technologies making it difficult for themselves to shift investment to disruptive innovations (see also Gans, 2016 and Christensen et al., 2015)[6]. As a result, trajectories of technological progress and industry structure in established markets change.

Whereas disruption discussed in the above literature leads to the erosion of incumbency advantages, strategic management literatures that stress firms' 'dynamic capabilities' suggest that the erosion of incumbency advantages may be limited. The dynamic capabilities of firms may favour incumbents with better access to finance and market know-how (for instance see Teece, 2007). According to O'Reilly and Tushman (2004), appropriate internal organisation of the firm can overcome managerial biases mentioned in the disruptive innovation literature. Ho and Chen (2018), by exploring the cases of Kodak and Fujifilm in the face of digital disruption, propose that incumbent firms could also succeed if they adopt disruptive innovations early and at the same time further exploit their sustaining competences.

We add to the disruptive innovation literature by providing new empirical evidence relating to the consequent market structure outcomes. Our empirical approach draws heavily on the

[6] The IO innovation literature also extensively analyses the different incentives to innovate between incumbents and challengers/entrants. Studies in this area often come from a different but related perspective compared with the disruptive innovation literature mentioned above. For instance, using data similar to Christensen and Rosenbloom (1995), Igami (2017) finds that the 'replacement effect' faced by an incumbent with market power, whose new products cannibalise profits already earned from their existing range explains why entrants were successful in the adoption of 3.5 inch over 5.25 inch hard disk drives in the 1980s. Based on a comprehensive survey of relevant theorical studies, Reinganum (1989) shows that the presence/absence of technological uncertainty in the production of innovation affects incumbents and entrants' timing of innovation differently.

industrial organisation literature on the evolution of market structure, due to Sutton (1991, 1998). This approach is reviewed in section 3.2. We find a large de-concentrating effect of internet banking, which suggests that new technology of such a disruptive nature has allowed the smaller challengers/entrants to erode some of the advantage of the large/established incumbents with legacy technology.

RQ3: What effect has the uptake of internet banking had on integration across previously regional markets?

Our methodology allows us to compare countries in which banks tended to have national coverage, with those in which regional banks were common. In addition to the '*de-concentrating effect'* mentioned above, our results suggest a consolidation force which we call the '*extended geographic reach effect'*. Internet banking erodes regional incumbent legacy advantages (e.g. the value of local branches), facilitating cross-regional entry, bank consolidation and the exit of weaker regional banks. Thus, the direction of travel is towards national market integration post internet banking.[7]

To the best of our knowledge, this is the first econometric study investigating the interaction between a potentially disruptive digital technology and these elements of market structure. Nevertheless, there is an interesting comparison between our work and that of Pelletier et al (2020). They study the spread of mobile money, weighing the competing capabilities of banks and international telecoms firms as initial innovators in emerging markets. They find that banks in developing countries had focussed on urban branch networks, with little coverage for the rural population, and were slow to introduce mobile banking products. In contrast, telecoms firms could provide low risk transactions execution services at the same time as they were expanding their rural mobile network coverage.

There are two relevant differences between their work and ours. First, Pelletier et al examine only the initial launch of mobile banking services by 'firms', whereas we also examine the speed of uptake of internet banking by consumers. Second, we examine European markets in which all geographic areas already had access to banking services, so there was no substantial unsupplied market for entrants to gain a foothold – internet

[7] Another market that started out with strong locally focussed firms, and which has been severely disrupted by digital products, is local newspapers. Their decline across much of the world has been well documented (see e.g., Abernathy, 2020 in the US, and Jenkins and Nielsen, 2018 in Europe). However, the two-sidedness of newspaper markets has resulted in a more complex dynamic. Revenues to fund journalism were traditionally generated both by selling print copy to local citizens and by selling advertising. Internet entry has affected both. Despite having grown their online audiences, local newspapers have had limited success in monetising through a paywall (partly due to consumer substitution into social media), and advertising revenues have been scooped up by Google, Facebook and other non-journalism sites. Unlike for the online banking product, local news in one part of the country is completely different to that in another locality so there is little scope for economies of scale/regional integration. Consequently, investment in quality local journalism has had to adjust more than market structure.

banking was an improvement in product delivery, not a completely new product like mobile banking in many emerging countries with large rural populations.

3. Modelling Approach and Model Specifications

3.1 Approach to modelling the user uptake of internet banking

Our approach is to adapt a classic contagion model of the user uptake of a new service, and then focus on how market structure may be expected – separately - to influence the timing and speed of diffusion.

We start from the standard logistic function first used by Griliches (1957) which describes how the technology diffusion process follows an S-shaped function: $IB_{it} = \frac{M_{it}}{1+e^{(-(a_{it}+b_{it}t))}}$,

where IB_{it} is the number of users that have adopted internet banking in country *i* at time t, M_{it} is the maximum number of potential users.

a_{it} shifts the logistic curve horizontally and is known as the location or timing parameter. Its economic interpretation in our context is that if we compare two countries at the start of our observation period, for similar b, the one which introduced internet banking earlier will have a higher a. Less formally, a can be interpreted an indicator of when sufficient banks had introduced internet banking for consumer 'contagion'/uptake to take off.

b_{it} is the slope of the diffusion curve, which is typically referred to as the speed of diffusion. It measures how rapidly new consumers adopt internet banking once it has been introduced. The logistic functional form means that this single parameter takes account of both limited consumer learning opportunities and word-of-mouth in the early years, and fewer potential new users once uptake becomes saturated, with maximum speed of uptake in between.

We next assume that the maximum possible uptake (saturation level) is a proportion, λ, of current internet usage, IU_{it}, so $M_{it} = \lambda * IU_{it}$.

Rearranging the logistic equation and taking logs gives the following equation:

$$\log\left(\frac{IB_{it}}{\lambda * IU_{it} - IB_{it}}\right) = a_{it} + b_{it} * t.$$

There are a number of ways how market structure might affect a_{it} and b_{it}. The early introduction of internet banking a_{it} may be facilitated by the immediate scale possibilities of converting existing customers to the internet service in a concentrated market. Once introduced, the speed of consumer uptake, b_{it}, will depend on the ability and incentive for banks to market their internet services. This suggests a range of factors relating to market structure that might influence consumer uptake. These may include the original introduction of internet banking services, investments in interface quality and security, ongoing marketing, price and the implicit price of branch banking (i.e. substitutes). Our reduced form approach bypasses these proximate influences, which anyway are almost impossible to measure at the market level.

Both a_{it} and b_{it} are also likely to be influenced by demand side factors such as income, education and demographic factors. Previous bank investments in branch networks also affect the availability and opportunity cost of using a close substitute for internet banking.

For our estimation, both a_{it} and b_{it} are allowed to be affected by market structure, including *concentration* (C_{it}) and *regionalisation* (R_i), *branch density* (B_{it}) and a vector of controls (X_{it}).[8] We therefore estimate the following equation:

$$\log\left(\frac{IB_{it}}{\lambda * IU_{it} - IB_{it}}\right) = a_0 + a_1 C_{it} + a_2 B_{it} + a_3 R_i + a_4 X_{it} + b_0 \mathrm{t} + b_1 C_{it} * t + b_2 B_{it} * t + b_3 R_i * t + b_4 X_{it} * t + u_{it} \quad (1)$$

Where u_{it} is the idiosyncratic error term. We explain our estimation strategy in Section 5.1, including how we deal with the potential endogeneity of *concentration* (C_{it}) and *branch density* (B_{it}).

3.2 Approach to modelling endogenous national concentration

Our approach to modelling endogenous market structure builds on a reduced form relationship between concentration and market size. In most markets, economies of scale lead to a negative relationship between concentration and market size in free entry equilibrium. But the slope and position of this relationship depends on factors such as the intensity of price competition[9], the degree of economies of scale, and the extent of entry barriers. For instance, for a given market size, tougher price competition results in a more concentrated market as reduced margins require more customers per firm in order to cover fixed costs. Horizontal product differentiation moderates these effects by reducing the intensity of price competition, but does not change the basic relationship.

In addition to horizontal differentiation, competition can also be channelled into the escalation of *endogenous sunk costs* characterised by quality-enhancing investments that benefit all consumers without raising marginal cost (e.g. denser branch networks in the pre-internet era).[10] As a result, an increase in market size may then have less effect on concentration (and prices) than on enhanced quality.[11] While it is theoretically possible that the relationship between concentration and market size may become positive, it is empirically more typical for the relationship to remain weakly negative but less steep in the presence of such quality competition.[12]

We expect high user adoption of internet banking to result in a more negative relationship between market size and concentration, i.e. a 'de-concentrating effect', counteracting the

[8] In addition to the observed heterogeneity determined by the factors (market structure, branch density and controls) mentioned above, unobserved heterogeneity relating to each of the parameter which is not taken into account in our estimation may also influence the location and speed parameters, therefore the process of diffusion. In this respect, the estimated location and speed parameters in our model should be viewed as mean estimates driven by the observed factors mentioned above.

[9] e.g. Bertrand or Cournot. See, for example, Shaked and Sutton (1987), Sutton (1991), Bresnahan & Reiss (1991) and Berry (1992).

[10] Previous studies (See Dick, 2007; Cohen and Mazzeo, 2010; Kim and Valie, 2001; Temesvary, 2015) have provided supportive evidence that branch investment in the pre-internet era could be a quality-enhancement investment characterised as endogenous sunk costs in banking.

[11] See Berry and Waldfogel (2010) for an empirical test of the difference between markets where quality is enhanced by endogenous sunk costs as compared with quality enhancements that increase marginal cost.

[12] See Sutton (1991, 1998). Sutton (2007) reviews the literature.

influence of higher endogenous sunk costs in legacy technology such as branch network invested by established incumbents.

We adopt a well-established functional form for the relationship between concentration and market size. Following Sutton (1991) and followers, we specify $y = \alpha + \frac{\beta}{\log S}$, where *y* is the logistic transform of the concentration ratio, *S* is national market size, and α and β are coefficients to be estimated.

We allow both α and β to vary with regionalisation, *R*, so we can test whether the relationship between concentration and market size differs between regionalised and non-regionalised markets.

Adding a time trend, *t*, gives

$$\log(\frac{C_{it}}{100-C_{it}}) = \theta_0 + \theta_1 t + \theta_2 \frac{1}{\log S_{it}} + \theta_3 R_i + \theta_4 R_i * \frac{1}{\log S_{it}} + \theta_5 B_{it} + \varepsilon_{it} \qquad (2)$$

where C_{it} is the five-firm concentration ratio, R_i is our regionalisation index, B_{it} is branch density, S_{it} is total national banking assets and $\theta_0, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5$ are coefficients to be estimated. ε_{it} is the idiosyncratic error term.

As mentioned above, our principal aim is to explore whether increasing user uptake of internet banking has had a de-concentrating effect. Such mechanisms are likely to operate slowly and not smoothly. Since we do not expect effects on concentration to happen either contemporaneously or with a simple time lag, we test a model that allows the relationship in equation (2) to shift once a threshold level of *IB* is reached. A dummy variable, *D*=1 for high *IB*, is interacted with all the right hand side variables in equation (2), so the coefficients can be interpreted as the incremental effect of a high level of internet banking on the determination of concentration. Writing the right hand side of equation (2) as $\gamma X_{it} + \varepsilon_{it}$, we estimate equation (3):

$$\log\left(\frac{C_{it}}{100-C_{it}}\right) = \gamma X_{it} + \delta D_{it} X_{it} + \varepsilon_{it} \qquad (3)$$

Our estimation strategy, including how we deal with the possible endogeneity of variables D_{it} and B_{it}, is explained in Section 5.2.

3.3 Construction of the regionalisation index

Some European countries have much more regionalised banking markets than others. The roots of these differences are historic; for example, where there were proud histories of independent states prior to nineteenth century unification (e.g. Germany, Italy). These countries tend to have lower national concentration than countries of a similar size but with nationally integrated banks. For example, in 2009 the combined market shares of the five largest banks in Estonia and the Netherlands were 93% and 85% respectively, while in the much more regionalised jurisdictions of Germany and Italy, this concentration ratio (C) was only 25% and 34%. Equations (1) and (3) should ideally be estimated at the level of the competitively relevant market, which may be regional in some countries and national in others. In the absence of consistent data at the level of relevant geographic markets, we use a measure of pre-internet banking regionalisation (R_i), based on the Herfindahl index of regional concentration of bank headquarters, explained as follows.

We began with the idea that banks tend to locate their central operations close to their main demand base. Thus, a strongly regional bank (in terms of its branch and customer base) is likely to be headquartered in the region where it is strong, whereas a bank that considers the whole country as its natural market is more likely to be headquartered in the national financial capital.

Consider a country with *K* regions. We require an index of regionalisation, *R*, with the following desirable properties.

1. Minimum $R = 0$ if all headquarters (HQs) are in a single region. This should apply for both a multi-region country and a small country which forms a single region.
2. *R* should increase if HQs are distributed more equally between a given number of regions ($K \geq 2$). Maximum *R* (given *K*) should result from a uniform distribution of HQs (i.e. a share K^{-1} in each region).
3. R should increase if, for a given distribution of HQs, the number of regions with HQs increases.

To develop our index, we aggregated the assets of all banks headquartered in region *k* to create the scale of banking in that region, S_k. The region's share of national banking assets is $\frac{S_k}{S}$ where $S = \sum_{k=1}^{K} S_k$. We propose the following index:

$$R = \left[1 - \sum_{k=1}^{K} \left(\frac{S_k}{S}\right)^2\right].$$

The summation term is a Herfindahl index of regional concentration of bank HQs, and the "one minus" converts this to an index of regionalisation. *R* ranges between zero (when all HQs are in one region), and $1 - K^{-1}$ (when there is an equal number of HQs in each region). Two empirically interesting examples are where: a) there are two equal sized regions and the remaining $K - 2$ regions have no HQs, in which case $R = 0.5$, and b) there are four regions containing 40%, 30%, 20% and 10% shares of HQs, in which case $R = 0.7$.[13] It is straightforward that *R* satisfies the first desirable property. The second and third follow from a standard property of the Herfindahl that $\sum_{k=1}^{K} \left(\frac{S_k}{S}\right)^2 = \frac{1+v^2}{K}$, where *v* is the coefficient of variation of regional shares.

It should be noted that even in regionalised markets, some competition might exist beyond region. Therefore, the above measure of pre-internet banking regionalisation could be viewed as a control of the national concentration which is associated with competition beyond regions within a nation. Whereas it is possible that competition may even exist beyond national boundary, in this paper we consider that the relevant geographic market is not wider than national (i.e. we have not considered market structure measures beyond national level). This is consistent with the European Commission's report regarding a Sector

[13] Of course, the same *R* can come about from many different distributions of HQs; e.g. one region with 68% and three with 11% each would give *R*=0.5.

Inquiry under Article 17 Regulation 1/2003 on retail banking[14] during which retail banking concentration was investigated both at national and regional levels (section 4 in the report).

4. Data Description

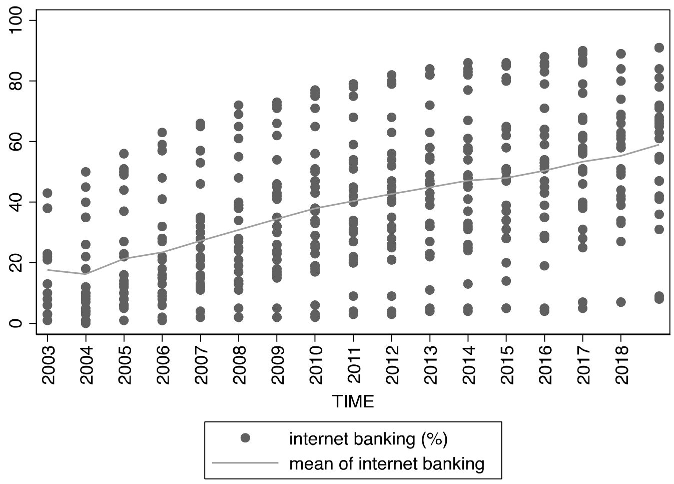
Our dataset consists of a panel of relevant variables 1997-2018 for the fifteen EU member states at the start of the period, increasing to 27 countries from 2001 (i.e. including the new members who acceded in 2004).[15] In this section we describe our data on key variables including internet banking, national concentration and regionalisation.

An annual Eurostat survey since 2003 has reported the percentage of surveyed individuals by EU Member State who have used internet banking in the past three months.[16] We use this as our measure of the user uptake of internet banking. Similarly, data on internet usage is collected from the same survey to measure individual who have used the internet in the past three months.

Figure 1 summarises the range of internet banking experiences across countries and the general trend. Each dot represents a Member State.

Two features stand out. First, the international variation is strikingly large. Second, the average increasing trend appears broadly consistent with an S-shaped diffusion.

Figure 1. Consumers using internet banking (by EU Member State)



[14] https://competition-policy.ec.europa.eu/sectors/financial-services/sector-inquiry-retail-banking_en (last checked 24 Feb 2023)

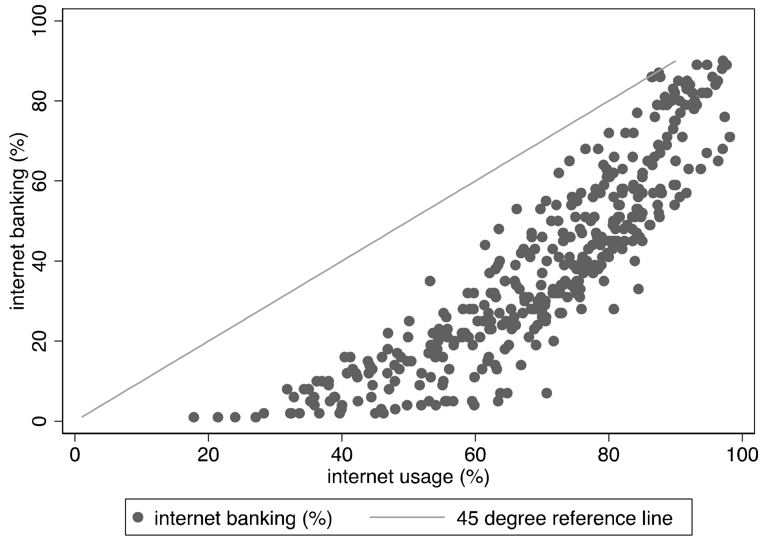
[15] The recently acceded member Croatia is not included in the sample.

[16] An overview of the dataset constructed by Eurostat can be found using the following link: https://ec.europa.eu/eurostat/web/products-datasets/-/tin00099 (last checked 24 Feb 2023). Internet banking includes electronic transactions with a bank for payment, transfers, etc. or for looking up account information. Further details regarding the survey questionnaire can be found in the Methodological Manual of Eurostat's Digital economy and society database : https://ec.europa.eu/eurostat/web/digital-economy-and-society/methodology (last checked 24 Feb 2023).

Source: Eurostat

Our assumption that the maximum possible uptake (saturation level) of internet banking is a proportion, λ, of current internet usage, IU_{it}, ($M_{it} = \lambda * IU_{it}$) is consistent with the data on internet banking and internet usage for all country-year pairs plotted in Figure 2, which shows that *IB* is bounded by *IU*.

Figure 2. Internet Banking vs. Internet Usage



We use data on national concentration collected by the European Central Bank (ECB), which publishes systematic data on banking activities for each EU Member State (whether or not it is in the Eurozone). The ECB data are for 'credit institutions' defined as businesses which either (i) receive deposits or other repayable funds from the public and grant credit on their own account, or (ii) issue means of payment in the form of electronic money.[17] We call these 'banks' for short.

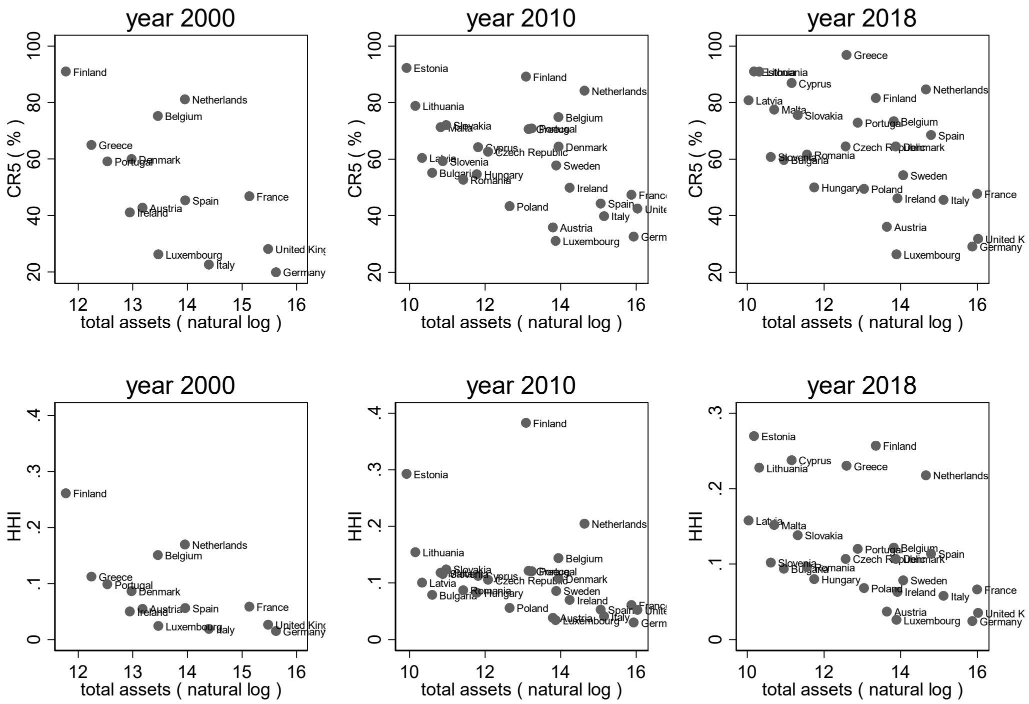
The ECB measures bank size by total assets. Importantly, total assets are calculated on a residence basis. Hence, this includes the activities of foreign banks in a particular Member State and excludes the foreign activities of domestic banks. The number of banks is similarly measured to include all credit institutions under the jurisdiction of each country, regardless of national or international ownership. The downside to using the ECB data is that it does not disaggregate by type of activity (e.g. retail versus investment banking), but we still consider the ECB data to be the most meaningful available in the context of consumer choice.

[17] Further details relating to the data description can be found from the database of Structural Financial Indicators constructed by ECB Statistical Data Warehouse: https://sdw.ecb.europa.eu/browse.do?node=9691551 (last checked 6 March 2023).

The ECB also measures market size by total assets and calculates two standard measures of national market structure: five-firm concentration ratio (*CR5*) and Herfindahl index (*HHI*). The relationship between the concentration ratio and market size is shown in Figure 3.

Three observations stand out. First, there is a very wide range of market sizes. Much of this is consistent with differences in population and the very different histories of the accession countries, but Luxembourg stands out as disproportionately large. This is likely to be due to the wide definition of banking used by the ECB, so we test our later results for sensitivity to excluding Luxembourg. Second, even markets of a similar size demonstrate a considerable range in concentration. Third, there appears to be a broadly negative relationship between concentration and market size, with a fairly well defined lower bound (especially if Luxembourg excluded).

Figure 3. Bank Concentration and market size



Source: ECB.

To measure regionalisation, as defined in Section 3.3, we collect information on each bank's headquarters location (including city and postcode) from the Banker database.[18] We include

[18] The ECB does not publish information on individual banks. The Banker Database was created as part of The Banker magazine's regular rankings of the world's largest banks. Owned by the Financial Times, it provides coverage of the leading banks in more than 190 countries. https://www.thebankerdatabase.com/index.cfm?fuseaction=lite.overview (last checked 6 March 2023). While not fully comprehensive, banks covered by the database represent more than 90% of the banking assets in each European country. Note that the coverage of banks in a given country may vary slightly over time due to merger, entry and exit. Our reported country index, as used in our econometrics is the average over time.

all banks at the group level (bank holding companies) [19] and use the postcode to identify the NUTS level 2 region in which each bank is headquartered.[20]

Table 1 reports our index of regionalisation based on bank assets for each country in our dataset.[21] In Cyprus, Estonia, Latvia, Lithuania, Luxembourg and Malta, there is only one NUTS2 region, so the index is zero. In Belgium, Bulgaria, Czech Republic, France, Hungary, Ireland and Slovakia, all banks covered in the sample are headquartered in one region, so our index is also zero for these countries. The countries with the most regionalised banking are Germany, Italy and Spain, each with $R \approx 0.7$. Austria, the Netherlands, Portugal and, to a lesser extent, the UK and Slovenia, have two strong HQ locations ($R \approx 0.5$) and the remaining countries have very asymmetric regionalisation around a dominant financial capital.

Table 1: Regionalisation within countries

Country	*R index*
Belgium, Bulgaria, Cyprus, Czech Republic, Estonia, France, Greece, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Malta, Slovakia Sweden	0
Poland	0.04
Finland	0.07
Denmark	0.2
Romania	0.26
Slovenia	0.38
United Kingdom	0.4
Austria	0.48
Netherlands	0.5
Portugal	0.53
Spain	0.68
Germany	0.69
Italy	0.7

Source: authors' calculations.

It is worth noting that the reported variation in the degree of regionalisation is consistent with the data presented in the European commission's Sector Inquiry on retail banking.[22]

[19] For instance, if a savings bank in Italy (such as Cassa di Risparmio di Carpi, Cassa di Risparmio di Trento e Rovereto (Caritro), Cassa di Risparmio di Trieste) joined Unicredit group, it would not be counted as a separate bank even though it might still have a local headquarter.

[20] Where postcode information was lacking, we matched the bank city with NUTS regions directly. The EU defines level 2 regions to mirror the territorial administrative divisions of Member States, each with populations generally in a band of 800,000 to 3,000,000. See (last checked 6 March 2023) https://ec.europa.eu/eurostat/web/nuts/principles-and-characteristics

[21] An alternative index based on the number of banks (rather than bank assets) was also constructed. It made no material difference to our descriptive or econometric results.

[22] https://ec.europa.eu/competition/sectors/financial_services/inquiries/retail.html (last checked 6 March 2023)

Full descriptions of all variables, their measurement and sources are given in Appendix 1 (Table A1 and A2).

5. Estimation and identification

5.1 Estimating the user uptake of internet banking

To allow for unobserved heterogeneity in equation (1), we follow the correlated random effects approach proposed in Wooldridge (2019), which is an extension of the well-established Chamberlain-Mundlak approach for balanced panel data to unbalanced cases. Under this approach, unobserved heterogeneity is allowed be correlated to the history of selection and the selected covariates. The averages of covariates over time where we observe a full set of data on the dependent and independent variables, $\overline{X_i}$ are therefore constructed.

Equation (1) becomes:

$$\log\left(\frac{IB_{it}}{\lambda * IU_{it} - IB_{it}}\right) = a_0 + a_1 C_{it} + a_2 B_{it} + a_3 R_i + a_4 X_{it} + b_0 \mathrm{t} + b_1 C_{it} * t + b_2 B_{it} * t + b_3 R_i * t + b_4 X_{it} * t + c_i + v_{it} \quad (4)$$

where the unobserved heterogeneity is assumed to be $c_i = \varphi + a_{10} * \overline{X_i} + a_{11} * \overline{t_i} + a_i$ and v_{it} is time varying unobserved heterogeneity.

If the panel data are balanced, Mundlak (1978) shows that the fixed effect (FE) estimator can be computed using pooled OLS from the original data with the time averages of the covariates added as additional explanatory variables. Wooldridge (2019) extends this result to the unbalanced cases. Estimating equation (4) with additional explanatory variables in c_i (i.e. the time averages of time varying covariates), using pooled OLS with all observations that have a full set of data on the dependent and independent variables, the coefficient vector on the time varying covariates is the same as that obtained from the FE estimator.

C_{it} and B_{it} must be viewed as potentially endogenous. We follow the Control Function approach in Wooldridge (2015) to eliminate the potential bias. First, we assume a linear reduced form for the endogenous variable Y_{it}, which could be *C* or *B*:

$$Y_{it} = \gamma_0 + \gamma_1 Z_{it} + \gamma_2 \overline{Z_i} + r_{it} \quad (5)$$

and obtain the OLS residual $\hat{r}_{it}$. $Z_{it} = (Z_{it1}, Z_{it2})$ where Z_{it1} are the exogenous variables in (4) including *t, R* and *X*, and Z_{it} are instruments for *C* or *B* which are excluded from (4).

As already argued, the theoretical and empirical relationship between *C* and market size is long established and robust. Also, the essential nature of the retail banking product means that market size depends on the size of population, so we use (the natural log of) population as our instrument for *C*. Furthermore, a bank's decision to open a branch in a particular location depends on the number of potential customers who live nearby, so we use (the natural log of) population density as our instrument for *B*. Note that there is no obvious reason why individual decisions to take up internet banking should be *directly* determined by either population size or population density, so the exclusion restrictions are likely to be satisfied.

We thus estimate the following equation:

$$\log\left(\frac{IB_{it}}{\lambda * IU_{it} - IB_{it}}\right) = a_0 + a_1 C_{it} + a_2 B_{it} + a_3 R_i + a_4 X_{it} + b_0 \mathrm{t} + b_1 C_{it} * t + b_2 B_{it} * t + b_3 R_i * t + b_4 X_{it} * t + d_1 \hat{r}_{it}^{C} + d_2 \hat{r}_{it}^{B} + d_3 \hat{r}_{it}^{C*t} + d_4 \hat{r}_{it}^{B*t} + c_i + v_{it} \quad (6)$$

where $\hat{r}_{it}^{C}$ and $\hat{r}_{it}^{C*t}$ are control functions (OLS residuals) obtained from the reduced form equations for C_{it} and $C_{it} * t$ respectively. Similarly, $\hat{r}_{it}^{B}$ and $\hat{r}_{it}^{B*t}$ are the control functions obtained from the reduced form equation for B_{it} and $B_{it} * t$.[23]

The control variable vector X_{it} includes *education* (measured as percentage of population aged 25-74 who have obtained tertiary education), *GDP per capita, median income, income inequality (Gini coefficient), median age and unemployment*. A full list of variables and data sources are shown in Appendix 1. We cannot estimate λ but expect it to be close to one and conduct a sensitivity analysis for lower values.

Since the estimation of equation (6) uses the estimated $\hat{r}_{it}$ instead of the true r_{it}, this extra source of variation has to be taken into account. To do so we implement the bootstrap as suggested by Wooldridge (2015). The significance levels reported below are based on bootstrapped standard errors.

It should be noted that the above estimation strategy employing the control function approach produces results identical to 2SLS estimation. As indicated by Wooldridge (2015), the advantage of using the control function approach is that it allows for a simple and robust test of endogeneity of the relevant (potentially endogenous) variables.

5.2 Estimating endogenous national concentration

To estimate equation (3), we construct the dummy variable $D = 1$ if $IB > \widetilde{IB}$ and 0 otherwise. $\widetilde{IB}$ is a threshold value we use to indicate whether an observation is *IB* intensive or not. We cannot directly estimate $\widetilde{IB}$ but use alternative candidate thresholds to test sensitivity. In our data sample, *IB* is only available from 2003. In year 2003, if the observation has *IB* below the threshold, then *D*=0 for all previous years. There are, however, a few countries whose level of *IB* is already above the threshold in 2003. In these cases, we use the first-stage probit model estimation (on the sample where we can determine all the values of *D*) to obtain the predicted probability of *D*=1 for all observations. If the predicted probability is greater than 50%, we set *D*=1 for these observations before 2003 and 0 otherwise. We then apply the first-stage regression again but with all observations to obtain the control function to be used for the second stage estimation.

As in section 5.1, we apply the correlated random effects approach to control for unobserved heterogeneity and the control function approach to control for potential endogeneity related to *S* and *B*. As explained earlier, we use the natural log of population size and population density as identifying instruments. All are highly significant in their respective first stage regressions. The control function enters equation (3) as $\delta_0 \hat{e}_{it}^{S}$ $\delta_1 \hat{e}_{it}^{S*R}$ and $\delta_2 \hat{e}_{it}^{B}$, to control for endogeneity of *S*, *S* interacted with *R*, and *B* respectively,

[23] The instrument for the interactive term of the endogenous variable with time is the selected instrument variable interacted with time.

where $\hat{e}_{it}^{S}$ $\hat{e}_{it}^{S*R}$ and $\hat{e}_{it}^{B}$ are estimated residuals from reduced forms of *S, S interacted with R* and *B* respectively.

We also need to control for a potential bias arising from the endogeneity of *D*, since *D* is constructed using *IB*. The following control function is adopted following Wooldridge (2015) using a first-stage probit regression to obtain a "generalised error" term defined as:

$\hat{e}_{it}^{D} = D\lambda(Z_{it}\delta) - (1-D)\lambda(-Z_{it}\delta)$ where $\lambda(.) = \phi(.)/\Phi(.)$ is the inverse Mills ratio and internet usage, *IU*, is used as an identifying instrument for *D.*[24]

It should be noted that *D* is interacted with other variables in equation (3). In models with multiple, nonlinear functions of endogenous variables (like our models, where endogenous variables are interacted with exogenous variables), Wooldridge (2015) points out the advantage of the control function approach in terms of its parsimonious way to account for endogeneity by including only one control function, compared with the standard IV approach using additional instruments (the interaction between instruments and the exogenous variables). He finds that the IV estimator is generally consistent, but the control function approach is more efficient.

For the above reason, we first adopt the control function approach including one control function $\hat{e}_{it}^{D}$ to exploit the efficiency of using one control function only. We then adopt the standard IV approach of 2SLS (equivalent to the control function approach including additional control functions associated with the endogenous variables interacted with other variables) as a consistency check. The results are both reported in Table 5, which suggest high consistency across the two approaches.[25]

6. Results

6.1 The user uptake of internet banking

First, consider econometric identification. First-stage regression results (not reported) confirm that our identifying instruments for *C* and *B*, population size and population density respectively, are both highly significant and contribute substantially to explaining the variance in these endogenous variables. Our estimates of equation (6) are reported in Table 2. As shown towards the bottom of the table, the control function for bank concentration $\hat{r}_{it}^{C}$ is significant. This confirms the value of investigating the endogeneity of concentration in section 5.2. The endogeneity of branch density is not confirmed, as $\hat{r}_{it}^{B}$ and its interaction

[24] All exogenous variables and instruments (including the time averages of covariates) used for reduced form of the IB equation are also included in the reduced form of the *B*, *S* and the interaction between *R* and *S* equations here in the first stage regression. 4 regressions were run to obtain four control functions in the first stage following Wooldridge (2015). All 4 regressions use the same set of exogenous regressors/instruments.
[25] The size of the banking sector was much more limited under the pre-1990 communist regimes of Eastern and Central Europe, and this might have had an effect on more recent levels of concentration. Although markets were opened up a decade before our sample period begins, we created a dummy variable for these countries and included it as an additional instrument for bank market size alongside population and our other exogenous variables. The effect of this dummy variable is significant in the first-stage regression, justifying its inclusion.

with time are insignificant. Although we report our results with both control functions, excluding those which are not statistically significant makes no substantive difference to the results in Table 2.

Turning to our main results, we start with the complete specification "Spec 1", then eliminate each insignificant interactive term one by one using F-tests to compare how well each reduced specification fits the data. We end up with the more parsimonious "Spec 2" on which we focus. There is very little difference whether we measure concentration by *CR5* or *HHI*, so we report both but focus our discussion on the former. We proceed by discussing significance before returning to quantitative effects.[26]

[26] We also ran 2SLS regressions for "Spec 2" using *CR5* and *HHI* as measures of market concentration. The estimated coefficients and significance levels are identical to the control function approach, as expected, except that the standard errors differ slightly. These estimates are not reported to avoid repetition.

Table 2: Estimation Results for the Diffusion of IB

Dependent variable: user uptake of IB	Concentration measured by *CR5* Spec 1	**Spec 2**	Concentration measured by *HHI* Spec 1	**Spec 2**
C (concentration)	0.047*** (0.0151)	0.048*** (0.0079)	7.199* (3.8037)	8.375*** (2.7339)
R (regionalisation)	1.805*** (0.5700)	1.723*** (0.3625)	0.792 (0.6020)	0.887** (0.3646)
B (branch density)	0.126 (0.1319)	0.073 (0.1001)	0.288** (0.1272)	0.217** (0.1023)
E (Education, %)	-0.013 (0.0216)	-0.038*** (0.0113)	-0.001 (0.0233)	-0.036*** (0.0117)
G (GDP per capita, log)	-0.170 (0.7579)	--	-0.142 (0.6947)	--
I (Median income, log)	0.325 (0.6031)	0.528** (0.1936)	0.355 (0.5880)	0.571** (0.2099)
Gi (Gini income, 0-100)	0.071** (0.0283)	0.082*** (0.0255)	0.053* (0.0278)	0.078*** (0.0246)
PA (Median age, log)	-2.584 (3.4694)	--	-5.739* (3.4353)	--
U (Unemployment, %)	-0.009 (0.0313)	0.025*** (0.0062)	-0.020 (0.0313)	0.025*** (0.0061)
t	0.194 (0.5827)	0.407*** (0.0530)	-0.084 (0.6437)	0.297*** (0.0468)
*C*t*	-0.001** (0.0007)	-0.001*** (0.0004)	-0.117 (0.2435)	-0.209 (0.1690)
*R*t*	-0.089*** (0.0359)	-0.083*** (0.0211)	-0.038 (0.0391)	-0.045** (0.0220)
*B*t*	-0.031*** (0.0108)	-0.027*** (0.0087)	-0.036*** (0.0099)	-0.031*** (0.0082)
*E*t*	-0.002 (0.0014)	--	-0.002 (0.0015)	--
*G*t*	0.006 (0.0408)	--	0.017 (0.0378)	--
*I*t*	0.018 (0.0432)	--	0.015 (0.0418)	--
*Gi *t*	-0.008*** (0.0018)	-0.009*** (0.0017)	-0.007*** (0.0018)	-0.008*** (0.0016)
*PA *t*	0.027 (0.1297)	--	0.017 (0.1501)	--
*U *t*	0.002 (0.0020)	--	0.003 (0.0020)	--
constant	-67.915** (34.6492)	-67.814** (34.3305)	-13.007 (32.3030)	-12.594 (31.7151)
$\hat{r}_{it}^{C}$	-0.066*** (0.0169)	-0.068*** (0.0141)	-12.829** (4.9540)	-14.005*** (4.1566)
$\hat{r}_{it}^{C*t}$	0.003*** (0.0011)	0.004*** (0.0009)	0.690** (0.3094)	0.782*** (0.2567)
$\hat{r}_{it}^{B}$	-0.029 (0.2938)	-0.024 (0.2844)	-0.187 (0.3082)	-0.117 (0.3028)
$\hat{r}_{it}^{B*t}$	0.027 (0.0221)	0.024 (0.0212)	0.033 (0.0230)	0.028 (0.0224)
Adjusted R^2	0.92	0.92	0.92	0.92
No. of Obs.	381	381	381	381
F test to compare spec 1 & spec 2 (5% critical value: 1.84)	0.67		1.51	

Table notes:

1. ***, **, and *indicate statistical significance at 1%, 5% and 10% respectively; standard errors are in brackets.
2. Control functions for the two endogenous variables *B* and *C* and their interactive terms with time are obtained in the first stage following Wooldridge (2015)[27].
3. All regressions include the time averages of all time varying explanatory variables in spec 1 to account for any fixed effects, except for the two variables of main interest which are *C* and *B*. *R* is of main interest too, but it is fixed over time. By using the Mundlak approach, we are able to control for fixed effects but can still investigate the effect of time fixed variables such as *R*.
4. Recall that we assume the maximum possible uptake (saturation level) is a proportion, λ, of current internet usage, IU_{it}, so $M_{it} = \lambda * IU_{it}$. The results reported here are for λ=1. We repeated our estimations using λ=0.95 and λ=0.90. The latter necessitated a slightly reduced sample, since our sample maximum ratio of internet banking to internet usage is 0.93. There was no substantial difference from our reported results.

Market structure has a highly significant and nuanced effect on user uptake of internet banking. National concentration has a significant positive effect on the 'location' parameter (early adoption by banks). This early adoption of internet banking may be facilitated by incumbents' response to competitive threats and their immediate scale possibilities of converting existing customers to the internet service in a concentrated market.

However, concentration has a negative effect on the subsequent speed of uptake by consumers. This is consistent with concentrated banks most invested in an expensive bricks-and-mortar network to be less aggressive in encouraging their customers to take up internet banking.

Regionalised countries appear less concentrated at the (measured) national level, but if consumers mostly use a regional bank, concentration at the competitively relevant regional market level will be much higher. After controlling for national concentration, we therefore expect the impact of regionalisation on the user adoption of internet banking to be qualitatively similar to that of market concentration. This is exactly what we find. An additional incentive for early adoption by regional banks is that internet banking gives access to a much larger pool of customers outside their home region. But this pool of customers may have less familiarity and trust in banks outside their region, which adds to delayed uptake (lower speed). Table 3 combines both location and speed effects to show the accumulated impact over time. It reveals that the early positive impact of regionalisation was eliminated by the end of our period.

[27] In the first stage, the regressions were run as follows. Our endogenous variables include C and B, and the time interactions with C and B. All the exogenous variables include instruments for C and B (which are population and population density), the time interactions with exogenous variables/instruments and the time average of all these variables. Four regressions were run to obtain four control functions in the first stage. All four regressions use the same set of exogenous regressors/instruments.

Table 3: Cumulative effect of regionalisation over time

t (year)	CE	SE
7 (2003)	1.143***	0.2307
8 (2004)	1.060***	0.2136
9 (2005)	0.977***	0.1973
10 (2006)	0.895***	0.1820
11 (2007)	0.812***	0.1680
12 (2008)	0.729***	0.1556
13 (2009)	0.646***	0.1452
14 (2010)	0.563***	0.1374
15 (2011)	0.480***	0.1324
16 (2012)	0.398***	0.1308
17 (2013)	0.315**	0.1326
18 (2014)	0.232*	0.1376
19 (2015)	0.149	0.1455
20 (2016)	0.066	0.1560
21 (2017)	-0.016	0.1684
22 (2018)	-0.099	0.1825

Table notes:

1. ***, **, and *indicate statistical significance at 1%, 5% and 10% respectively.
2. The above are coefficients of R (regionalisation) varying with time, estimated from Specification 2 with *CR5* in Table 2.

Figures 4a and 4b illustrate the substantial quantitative effect of market structure, and the combined effects of concentration and regionalisation. The figures use the estimated coefficients from Table 2 to predict internet banking uptake for three illustrative levels of the concentration ratio (25%, 50% and 75%) and two of regionalisation (R = 0 and R = 0.7). The higher value is a natural choice since it applies to Germany, Italy and Spain.

First consider Figure 4a. We start with the second row. Panel *d* shows how uptake in a non-regional, low-concentration market proceeds over the sample period, increasing from 8% in 2003 to 60% in 2018. Panels *e* and *f* show how uptake increases with concentration (from low to medium and to high). For example, for three hypothetical countries with the same characteristics other than concentration, panel *f* shows that the high concentration country would achieve 50% consumer uptake in 2008, the medium concentration country in 2013 and the low concentration country in 2016. The earlier introduction in higher concentration countries is not overtaken by the faster speed of uptake in lower concentration countries before they converge near market saturation. Meanwhile, a 25% point higher concentration ratio could bring forward consumer benefits from internet banking by 3-5 years.

A similar effect of concentration in regionalised markets is seen by comparing across panels *a*, *b* and *c*. Note that in all cases the accumulated years of delay due to market structural factors, and consequently foregone consumer surplus, are substantial.

Figure 4a: Predicted internet banking uptake: the impact of concentration given each level of regionalisation

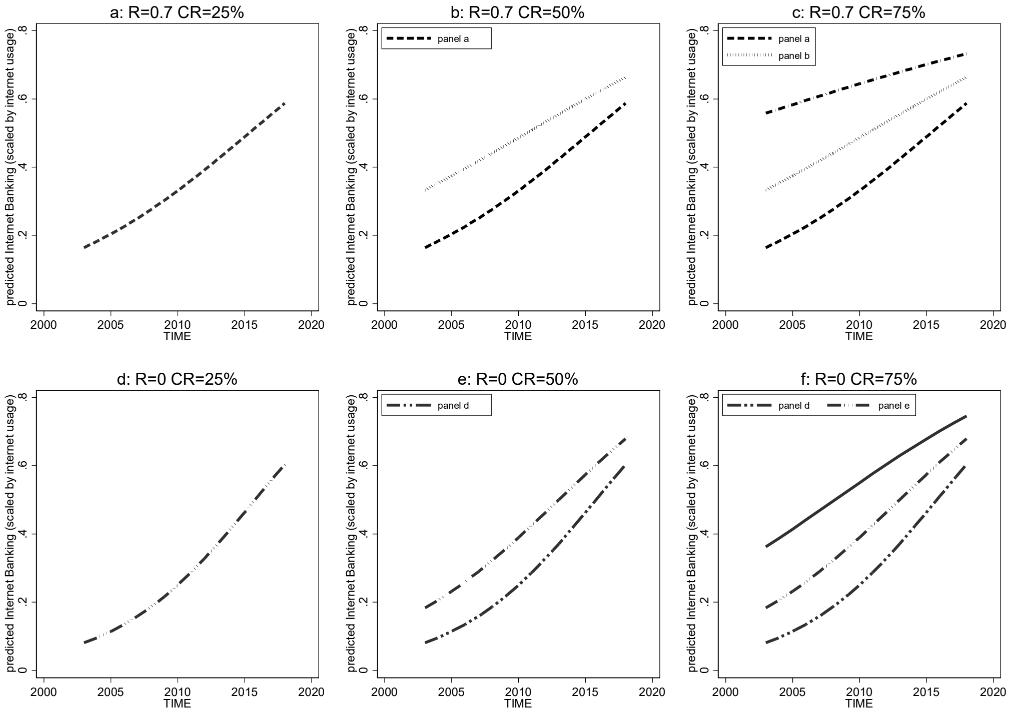
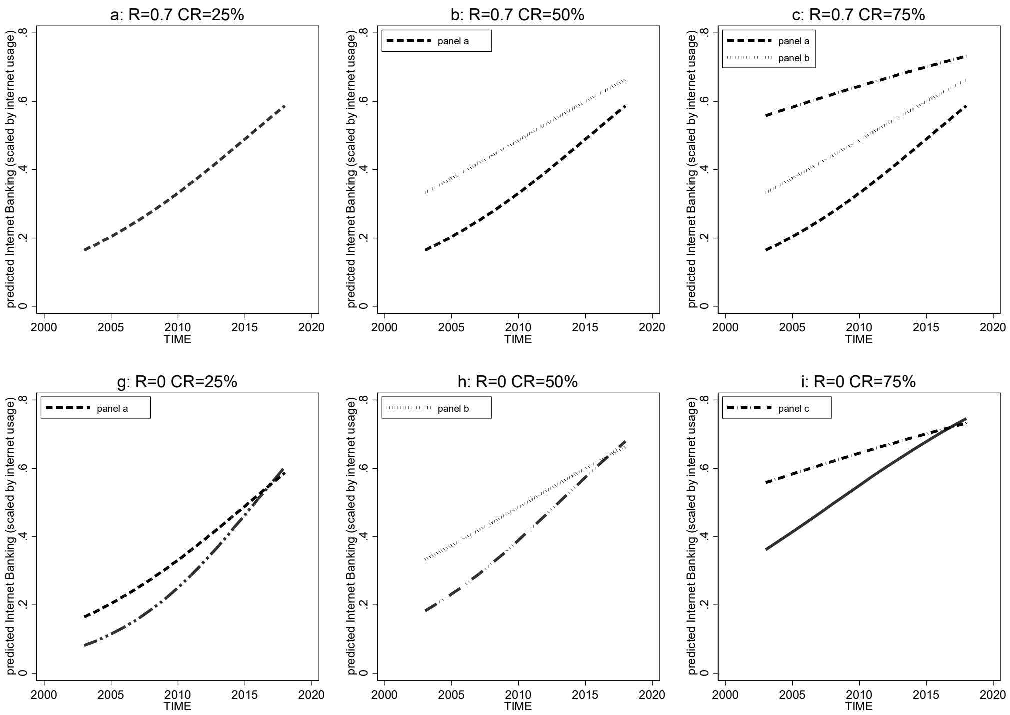


Figure 4b: Predicted internet banking uptake: the impact of regionalisation given each level of concentration



Notes: 1. R refers to Regionalisation; CR refers to the 5-firm concentration ratio; 2. The predicted adoption of internet banking is based on the model estimates from Spec 2 in Table 2.

The effects of regionalisation are most clearly seen in Figure 4b. Regionalised markets are shown in the first row, and the second row compares them with non-regionalised markets. For all levels of concentration, regionalised markets had an earlier adoption of internet banking, but this advantage had disappeared by the end of our sample period.

Returning to Table 2, there is significant evidence that high branch density, *B*, slows down the speed of user uptake. This is consistent with consumers who have easy access to a local branch also seeing less advantage in internet banking. The effect of *B* on initial introduction is inconclusive. It is insignificant when *CR5* is used as the concentration measure, but the *HHI* results suggest a positive effect on earlier introduction.

Of our remaining variables, the independent time trend is positive, as expected in any diffusion model. Median Income brings forward the introduction of internet banking but has no significant effect on the subsequent speed of uptake. Income inequality similarly incentivises introduction but thereafter reduces the speed of uptake. In combination, these consumer income effects suggest that richer consumers are earlier adopters. Having controlled for income effects, education and employment both have a negative impact on the initial introduction with insignificant effects on the speed of adoption.

6.2 Endogenous market concentration

Table 4 reports the results from our estimation of equation (3). We report results for a candidate threshold effect for internet banking to have a substantial effect on concentration of $\widetilde{IB} = 25\%$. Results for $\widetilde{IB} = 30\%$ are reported in Appendix 3 alongside other robustness checks. The alternative thresholds do not materially change our estimates.

We include a control variable (*A*) motivated by the financial crisis that arose in the middle of our sample period. This could potentially have been a confounding factor with an impact on concentration at a time of rising internet banking uptake. There was considerable variation in the extent to which the financial crisis hit different European banks and at what time. Identification is aided by the fact that this pattern was not closely correlated with internet banking uptake. We measure the extent of crisis by the total amount of state aid used by EU Member States, as published by the European Commission. More precisely, our measure is the cumulative total amount of aid in the form of recapitalisation and impaired asset relief relative to market size (measured by total assets). As expected, this control variable does significantly increase concentration in our sample.

Next, consider the significance of the control function errors reported at the bottom of the first set of results in Table 4. $\hat{e}_{it}^{B}$ is highly significant and with a negative coefficient, which confirms the endogeneity of branch density. There is similar evidence that the size of the banking sector (measured by assets) is also endogenous. The control function error term for the internet banking threshold is not significant. The second column reports 2SLS estimates. The results are similar to our control function (CF) estimates so we focus on the first column.

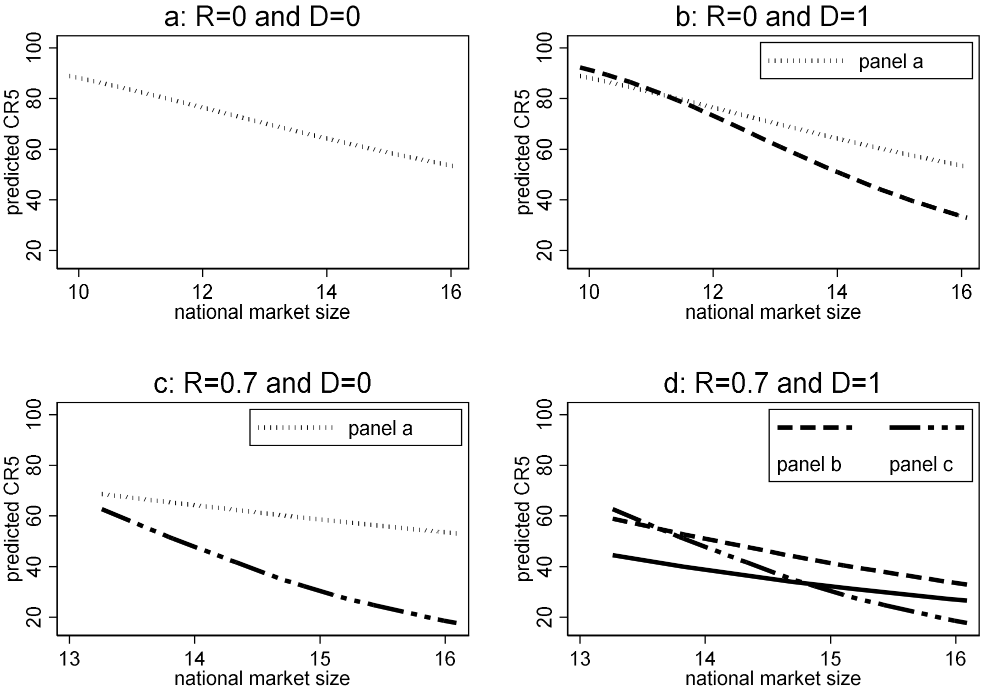
Consider our “pre-internet banking” estimates (i.e. for *D*=0). All variables are highly significant. As expected, concentration falls with both market size and regionalisation, and regionalisation has a stronger effect in larger countries. We also find that a dense branch network appears to have been an entry barrier and is associated with high concentration. Bearing in mind that we use an inverse measure of market size in our estimation, the 'de-concentrating' effect of internet banking (discussed below) is supported by the statistical significance of *D* and its interaction with market size.

Table 4 Estimation results for national concentration in banking

Dependent variable: $\log\left(\frac{C_{it}}{100-C_{it}}\right)$	*Estimated coefficients CF*	*Estimated coefficients 2SLS*
t	0.090***	0.081***
	(0.0082)	(0.0113)
$\frac{1}{\ln S_{it}}$	49.706***	58.581***
	(7.4198)	(7.6082)
R_i	-11.674***	-8.038***
	(2.1856)	(1.7908)
B_{it}	0.286***	0.259***
	(0.0670)	(0.0688)
$R_i * \frac{1}{\ln S_{it}}$	149.774***	98.528***
	(30.1833)	(24.1566)
D	-2.058***	-1.368*
	(0.5838)	(0.8381)
*D**t*	-0.090***	-0.077***
	(0.0101)	(0.0144)
$D * \frac{1}{\ln S_{it}}$	31.362***	20.863***
	(6.4704)	(9.8031)
$D * R_i$	13.119***	7.686***
	(2.5263)	(2.4002)
$D * B_{it}$	-0.159***	-0.154**
	(0.0615)	(0.0700)
$D * R_i * \frac{1}{\ln S_{it}}$	-179.961***	-101.104***
	(36.7303)	(33.7451)
A (crisis)	9.572***	8.355***
	(2.0891)	(2.7722)
Constant	3.706	3.884
	(3.1020)	(4.0957)
$\hat{e}_{it}^{S}$	-8.587	
	(16.3207)	
$\hat{e}_{it}^{B}$	-0.981***	
	(0.0883)	
$\hat{e}_{it}^{D}$	-0.128	
	(0.0937)	
$\hat{e}_{it}^{R*S}$	-199.214***	
	(35.9062)	
Adjusted R^2	0.77	0.65
No of Obs.	430	430

Table notes: Standard errors in brackets. ***, **, and * indicate statistical significance at 1%, 5% and 10% respectively.

Figure 5: Predicted market concentration varying with different levels of regionalisation and maturity of internet banking



Note: national market size is measured by the natural log of total assets (instrumented by population); *R* refers to Regionalisation and *D* refers to the dummy constructed to indicate pre or post internet banking era; *D*=1 indicates post internet banking and 0 otherwise; predicted *CR5* (concentration ratio) is based on model estimates from Table 5. The size of regionalised markets in our sample is relatively large. To enable the comparison without too much extrapolation, we have adjusted the scale of national market size for panels *c* and *d*.

In order to understand the quantitative effects of internet banking, it is helpful to consider Figure 5. We use Table 4 estimates to compute and plot the predicted relationship between concentration and national market size, with *t* and *B* set at their mean values. Each panel combines two values of *D* and *R*. We compare combinations of pre internet banking (*D*=0) and post internet banking (*D*=1), and non-regionalised markets (*R*=0) and regionalised markets (*R*=0.7).

Consider the non-regionalised markets (comparing panels *a* and *b*). Internet banking has substantially reduced concentration but only in larger markets. This 'de-concentrating effect' is consistent with internet banking eroding incumbency advantages (e.g. branch network) and encouraging entrants and/or expansion of challengers. More generally, following Sutton (1991), the steeper slope of the concentration-market size curve implies that quality competition after internet banking involves less costly escalation of sunk costs as compared with a competitive process that focuses on a bricks-and-mortar network.

Next, consider regionalised markets. The comparison between panels *c* and *d* shows internet banking has reduced concentration in small and medium markets, but not in the larger markets (such as Germany, Italy and Spain). This can be interpreted in terms of two distinct effects working against each other: a within-region de-concentrating technology effect with reduced importance of the branch network (as for non-regionalised countries); and an 'extended geographic reach' effect out of the home region raising competition, which results in bank consolidation and exit. Comparing panels *c* and *d*, we find that the net effect is that internet banking reduces national concentration in smaller countries with regionalised markets but raises national concentration in larger regionalised markets.

Finally, comparing panels *a* and *c*, we can see the very large difference between concentration in integrated markets and regionalised markets pre internet banking, particularly in large markets. Further comparison with panels *b* and *d* shows how internet banking has substantially closed that gap.

7. Robustness checks

We considered a number of robustness checks relating to the cut-off for internet banking in the concentration estimation, a possible outlier country (Luxembourg), and 2SLS estimation. Considering that branch density (as measured in our study) can vary significantly within a country dependent on the size of the urban versus rural areas, we included an additional instrument for both models (the natural log of metropolitan areas in each Member State). In each case, we re-ran our estimations using alternative assumptions and compared the results with those presented in the main text. Detailed results and explanations are available in Appendices 2, 3 and 4.

8. Conclusions

In this paper, we have tried to understand the market effects of digital product disruption by examining the co-evolution of market structure and the consumer uptake of a new product technology. Our econometric models investigate the consequences of market concentration and bank regionalisation for the adoption of internet banking, and vice versa. This required us to use a range of identification strategies as discussed in section 5. We are not aware of any previous literature that has tried to examine this co-evolution, but our results suggest it is important to do so.

Our first set of results relate to how market structure affects both digital product introduction and consumer acceptability of the new product. We find that banks introduce internet banking earlier in more concentrated markets, but then the speed of consumer uptake is slower than in less concentrated markets. We interpret this as firms with loyal customer bases in concentrated markets seeking to pre-empt entry or expansion of smaller incumbents, but then not investing so creatively to convert their existing customers to the internet. Our simulations show that the former effect (early introduction) outweighs the latter (slower uptake), with catch-up only as the market becomes saturated. Consequently, within the range of observed concentration levels, there may be as much as an eight-year delay in achieving a 50% consumer uptake in low concentration markets. Although this estimate assumes all other relevant variables are held constant and compares only hypothetical countries, it does suggest a very substantial loss of potential consumer surplus. In reality, this effect is partially mitigated in that low concentration banking markets (measured at the national level) also tend to be very regionalised, and the latter is shown to have a similar effect to higher concentration.

Our second set of results addresses the longer-term impact of internet banking on the evolution of market structure. This is an ongoing process as market structure evolves slowly, and the versatility of and trust in internet banking develops over time. Our sample period is also short of observations for when consumer uptake is saturated, so our results are best interpreted as directions of travel. We find a 'deconcentrating effect' of internet banking as it facilitates entry and expansion of smaller banks who can compete without needing to invest so heavily in expensive bricks-and-mortar networks.

We also find significant differences in the market structure effects of internet banking in countries with initially regionalised banks, as compared with those that started from a more unified national market. We identify an 'extended geographic reach effect' of internet banking because different regional banks are enabled to compete in each other's regions. This drives a process of consolidation and exit that tends to increase concentration at the national level, even as it strengthens competition within each region. We find that the deconcentrating effect outweighs the extended geographic reach effect in small countries, but the reverse holds for large countries.

Taken together, our results show how disruptive a new product technology can be, even when that technology is equally available to incumbents and entrants. In the case of internet banking, concentration facilitated a more rapid rollout of this fairly generic new product, but this new product ultimately resulted in the erosion of that concentration (or dominance).

References:

Abernathy, P. M., 2020. News deserts and ghost newspapers: Will local news survive? The University of North Carolina Pres, https://tinyurl.com/AbernathyNewsDeserts

Berry, S.T., 1992. Estimation of a Model of Entry in the Airline Industry. *Econometrica*, 60(4): 889-917

Berry, S., and Waldfogel, J., 2010. Product Quality and Market Size. *The Journal of Industrial Economics* LVIII.1: 1–31.

Bresnahan, T.F. and Reiss, P.C., 1991. Entry and Competition in Concentrated Markets, *Journal of Political Economy* 99: 977–1009.

Christensen, C.M., Rosenbloom, R.S., 1995. Explaining the attacker's advantage: technological paradigms, organizational dynamics, and the value network. *Research Policy* 24, 233–257.

Christensen, C.M., Raynor, M.E. and McDonald, R. 2015. What is disruptive innovation?, *Harvard Business Review*, https://hbr.org/2015/12/what-is-disruptive-innovation

Cohen, A.M. and Mazzeo, M.J., 2010. Investment strategies and market structure: an empirical analysis of bank branching decisions. *Journal of Financial Services Research* 38, 1–21.

Dick, A., 2007. Market size, service quality, and competition in banking. *Journal of Money, Credit, and Banking* 39: 49–81.

Gans, J., 2016. The Other Disruption, *Harvard Business Review*

Genakos, C., Valletti,T. and Verboven. F., 2018. Evaluating market consolidation in mobile communications. *Economic Policy*, 33 (93): 45–100

Griliches, Z., 1957. Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica* 25: 501–522.

Gruber, H., Verboven, F., 2001a. The Diffusion of Mobile Telecommunications Services in the European Union. *European Economic Review* 45, 577–588.

Gruber, H., Verboven, F., 2001b. The evolution of markets under entry and standards regulation – the case of global mobile telecommunications. *International Journal of Industrial Organization* 19, 1189–1212.

Ho, J.C. and Chen, H., 2018. Managing the Disruptive and Sustaining the Disrupted: The Case of Kodak and Fujifilm in the Face of Digital Disruption. *Review of Research Policy* 35 (3) 10.1111/ropr.12278

Hoenig, J.M., & Heisey, D.M., 2001. The abuse of power: The pervasive fallacy of power calculations in data analysis. *The American Statistician* 55: 19–24.

Igami, M. 2017. Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981–1998, *Journal of Political Economy* 125(3) : 798-847.

Jenkins, J. and Nielsen,R.K., 2018. The digital transition of local news*. Reuters Institute Digital News Report.*

Li, Y. and Lyons, B. 2012. Market structure, regulation and the speed of mobile network penetration. *International Journal of Industrial Organization* 30, 697-707

Mundlak, Y., 1978., On the Pooling of Time Series and Cross Section Data. *Econometrica* 46 (1), 69-85

Nickerson, D. and Sullivan, R., 2003. Financial Innovation, Strategic Real Options and Endogenous Competition: Theory and an Application to Internet Banking, Payments System Research. *Federal Reserve Bank of Kansas City Working paper* 03-01.

O'Reilly C.A. and M.L. Tushman, 2004. The Ambidextrous Organization, *Harvard Business Review* 82(4), 74-81.

Pelletier, A., S. Khavul and S. Estrin, 2020. Innovations in emerging markets: the case of mobile money. *Industrial and Corporate Change*, Vol. 29, No. 2, 395–421

Reinganum, J.F., 1989. "The timing of innovation: Research, development, and diffusion," in: R. Schmalensee & R. Willig (ed.), *Handbook of Industrial Organization*, edition 1, volume 1, chapter 14, 849-908, Elsevier.

Schulz, K.F., & Grimes, D.A., 2005. Sample size calculations in randomized trials: Mandatory and mystical. *Lancet* 365:1348–53.

Shaked, A. and Sutton, J., 1987. 'Product Differentiation and Industrial Structure,' *Journal of Industrial Economics*, 36.

Sullivan, R. and Wang, Z., 2013. Internet banking: An exploration in technology diffusion and impact. *The Federal Reserve Bank of Richmond Working Paper* No. 13-10.

Sutton, J., 1991. *Sunk costs and market structure: price competition, advertising, and the evolution of market structure*. MIT Press, Cambridge, MA.

Sutton, J., 1998. *Technology and Market Structure*. MIT Press.

Sutton, J., 2007. Market Structure: Theory and Evidence, in *The Handbook of Industrial Organization*, Volume 3, Armstrong, M. and Porter, R., eds. Elsevier, 2301-2368.

Takieddine,S. and Sun, J., 2015. Internet banking diffusion: A country-level analysis, *Electronic Commerce Research and Applications*, 14(5), 361-371

Teece, D. J. 2007. 'Explicating dynamic capabilities: the nature and micro foundations of (sustainable) enterprise performance,' *Strategic Management Journal*, 28(13), 1319–1350

Temesvary, J., 2015. 'Dynamic branching and interest rate competition of commercial banks: Evidence from Hungary' *International Journal of Industrial Organization*, 43, 98–110

The Furman Review. 2019. Unlocking digital competition, *Report of the Digital Competition Expert Pane*, HM treasury, https://www.gov.uk/government/publications/unlocking-digital-competition-report-of-the-digital-competition-expert-panel

Wooldridge, J.M., 2015. Control Function Methods in Applied Econometrics. *The Journal of Human Resources* 50 (2).

Wooldridge, J. M., 2019. Correlated random effects models with unbalanced panels. *Journal of Econometrics* 211.1, 137-150. https://doi.org/10.1016/j.jeconom.2018.12.010

Appendices

Appendix 1 Data Description

Table A1: Variables and sample used for the diffusion of internet banking model

	mean	min	max	sd	cv	N	definition	source
CR5 (%)	60.70	21.99	98.55	17.86	0.29	381	Concentration ratio of the largest 5 banks	ECB Statistical Data Warehouse (Publications/Reports/Financial Corporations/Structural Financial Indicators)
HHI	0.11	0.02	0.40	0.07	0.65	381	Herfindahl-Hirschman Index	ECB Statistical Data Warehouse (Publications/Reports/Financial Corporations/Structural Financial Indicators)
R	0.18	0.00	0.70	0.25	1.41	381	Bank Regionalisation	Calculated using bank headquarter information from Banker Database
B (natural log)	-3.39	-6.12	-0.99	1.12	-0.33	381	Branch density: number of branches per km^2	ECB Statistical Data Warehouse (Publications/Reports/Financial Corporations/Structural Financial Indicators)
IB (%)	39.08	1.00	90.00	23.71	0.61	381	Internet banking usage: the proportion of individuals who used the Internet banking in the last three months.	Eurostat: Digital Economy and Society
IU (%)	69.69	17.80	98.14	16.99	0.24	381	Internet usage: the proportion of individuals who used the Internet in the last three months.	Eurostat: Digital Economy and Society
PD (natural log)	4.64	2.74	7.32	0.91	0.20	381	Population density: population per km^2	Eurostat: Population and Social Conditions
Population (natural log)	8.92	6.00	11.32	1.42	0.16	381	population	Eurostat: Population and Social Conditions
GDP per capita (natural log)	10.13	9.14	11.30	0.38	0.04	381	GDP per capita	Eurostat: Economy and finance

Median age (natural log)	3.70	3.50	3.84	0.06	0.02	381	Median age of the population	Eurostat: Population and Social Conditions
Median income (natural log)	9.43	7.93	10.37	0.49	0.05	381	Median income of the population	Eurostat: Population and Social Conditions
Gini coefficient of income (0-100)	29.86	20.90	40.20	4.00	0.13	381	Gini coefficient of equivalised disposable income before social transfers	Eurostat: Population and Social Conditions
unemployment rate	8.64	4.29	2.20	27.50	3.18	381	Unemployment rate as a percentage of active population	Eurostat: Population and Social Conditions
Education (%)	24.48	9.90	40.50	7.43	0.30	381	The percentage of population aged 25-74 who have obtained Tertiary education	Eurostat: General and regional statistics

Table A2: Variables and sample used for the endogenous market concentration model

	mean	min	max	sd	cv	N	definition	source
CR5 (%)	59.19	18.95	97.28	18.57	0.31	430	Concentration ratio of the largest 5 banks	ECB Statistical Data Warehouse (Publications/Reports/Financial Corporations/Structural Financial Indicators)
TA* (natural log)	13.00	9.49	16.12	1.76	0.14	430	Total assets from the aggregated balance sheet of MFIs (excluding national central banks)	ECB Statistical Data Warehouse (Publications/Reports/Money, Credit and Banking/MFI balance sheet)
R	0.20	0.00	0.70	0.26	1.32	430	Bank Regionalisation	Calculated using bank headquarter information from Banker Database
B (natural log)	-3.30	-6.12	-0.99	1.12	-0.34	430	Branch density: number of branches per $Km^{2.}$	ECB Statistical Data Warehouse (Publications/Reports/Financial Corporations/Structural Financial Indicators)
D	62% of observations with D=1 when IB threshold is at 25%					430	Dummy variable to indicate internet banking penetration	Constructed using data on Internet banking (IB)
IU (%)	69.26	16.00	98.00	18.11	0.26	377	Internet usage: the proportion of individuals who used the Internet from any location in the last three months	World development indicator database
PD (natural log)	4.68	2.72	7.32	0.91	0.19	430	Population density: population (in thousands) per km^2	Eurostat: General and regional statistics
Population (natural log)	9.07	6.00	11.32	1.41	0.16	430	Population (in thousands)	Eurostat: general and regional statistics

A (crisis, deflated by total assets)	0.01	0.00	0.16	0.02	2.30	430	Accumulative total amount of state aid in the form of recapitalisation and impaired asset relief deflated by total assets	European Commission: https://ec.europa.eu/competition/state_aid/scoreboard/index_en.html

*Total assets data is obtained from the aggregated balance sheet of MFIs (excluding national central banks) by country. MFIs are defined as central banks and other MFIs which comprise credit institutions, deposit-taking corporations other than credit institutions, and money market funds. Ideally, we would like to have total assets measured by the aggregated balance sheet of all credit institutions only in a given country to be consistent with our banking market structural measures. But due to the lack of consistent data across all years and all countries, we use the data from the aggerated balance sheet of all MFIs. The share of total assets of all credit institutions in the whole euro area account for about 97% of total assets of all MFIs in 2018. Therefore, we think using total assets from MFIs would be a representative and good proxy of total assets of credit institutions.

Appendix 2: Robustness check for the estimation of the user uptake of internet banking

Considering that B (branch density, measured by the natural log of the number of branches per square km) could vary significant within a country depending on the size of urban areas as opposed to rural areas, ideally we would like to use data on the number of branches per square km in urban and rural areas separately. However, such information is not available. To mitigate potential bias caused by the omission of such variables, we constructed an additional instrument for B (branch density) measured by the natural log of the size of metropolitan land area (km^2) in the first stage regressions. We then repeated the analysis in the 2nd stage and reported the results in the following Table A3. The results are very consistent with what was shown in Table 2 in section 6.

Table A3: Estimation Results for the Diffusion of IB, without and without additional instrument for branch density

Dependent variable: user uptake of IB	C measured by C5 Spec 2 with additional instrument for B (branch density)	 Spec 2 without additional instrument for B (branch density)	C measured by HHI Spec 2 with additional instrument for B (branch density)	 Spec 2 without additional instrument for B (branch density)
C (concentration)	0.041***	0.048***	8.452***	8.375***
	(0.0063)	(0.0079)	(1.3877)	(2.7339)
R (regionalisation)	1.418***	1.723***	0.724**	0.887**
	(0.3753)	(0.3625)	(0.3204)	(0.3646)
B (branch density)	0.064	0.073	0.237***	0.217**
	(0.0860)	(0.1001)	(0.0867)	(0.1023)
E (Education,%)	-0.024**	-0.038***	-0.030***	-0.036***
	(0.0110)	(0.0113)	(0.0098)	(0.0117)
I (Median income	0.527***	0.528**	0.628***	0.571**
(log)	(0.1733)	(0.1936)	(0.1722)	(0.2099)
Gi (Gini income , 0-	0.105***	0.082***	0.090***	0.078***
100)	(0.0224)	(0.0255)	(0.0220)	(0.0246)
U	0.023***	0.025***	0.024***	0.025***
(Unemployment, %)	(0.0059)	(0.0062)	(0.0057)	(0.0061)
constant	-68.299**	-67.814**	3.970	-12.594
	(28.0282)	(34.3305)	(28.4343)	(31.7151)
t	0.354***	0.407***	0.288***	0.297***
	(0.0403)	(0.0530)	(0.0355)	(0.0468)
*C*t*	-0.007**	-0.001***	-0.095	-0.209
	(0.0004)	(0.0004)	(0.0883)	(0.1690)
*R*t*	-0.059***	-0.083***	-0.033*	-0.045**
	(0.0219)	(0.0211)	(0.0192)	(0.0220)
*B*t*	-0.029***	-0.027***	-0.033***	-0.031***
	(0.0072)	(0.0087)	(0.0071)	(0.0082)
*Gi *t*	-0.010***	-0.009***	-0.009***	-0.008***
	(0.0015)	(0.0017)	(0.0015)	(0.0016)
$\hat{r}_{it}^{C}$	-0.053***	-0.068***	-11.115***	-14.005***
	(0.0114)	(0.0141)	(2.9895)	(4.1566)
$\hat{r}_{it}^{C*t}$	0.002**	0.004***	0.258	0.782***
	(0.0007)	(0.0009)	(0.2269)	(0.2567)
$\hat{r}_{it}^{B}$	0.351	-0.024	0.189	-0.117

	(0.2525)	(0.2844)	(0.2813)	(0.3028)
$\hat{r}_{it}^{B*t}$	0.033*	0.024	0.035*	0.028
	(0.0192)	(0.0212)	(0.0209)	(0.0224)
Adjusted R^2	0.93	0.92	0.93	0.92
No. of Obs.	381	381	381	381

Figure A1. Predicted internet banking uptake: the impact of concentration given each level of regionalisation from Table A3

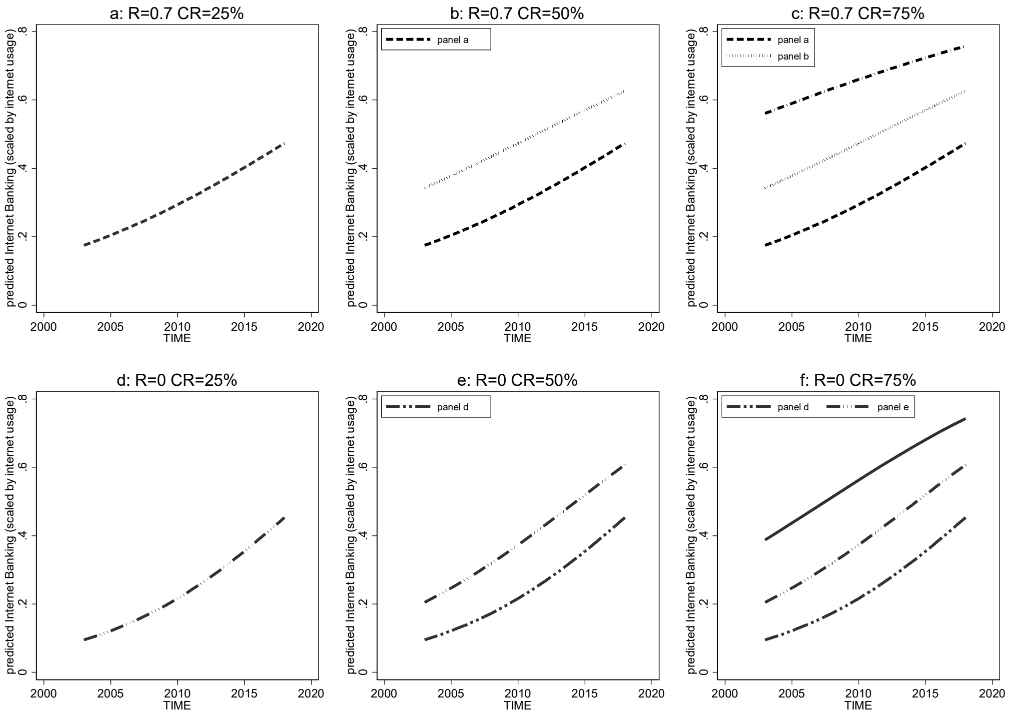
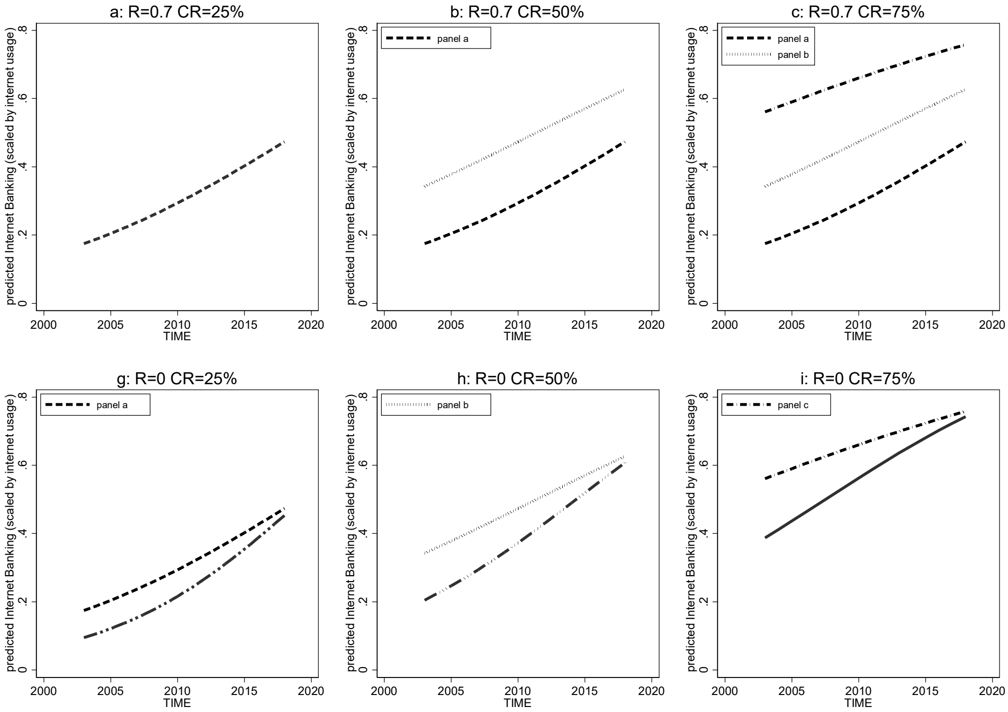


Figure A2. Predicted internet banking uptake: the impact of regionalisation given each level of concentration from Table A3

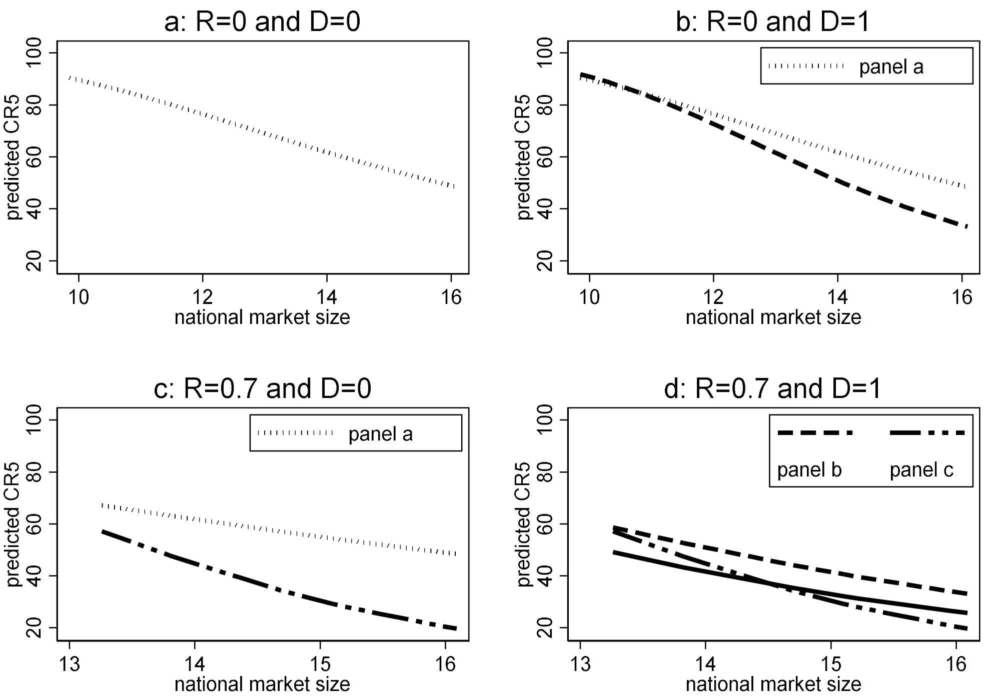


Appendix 3: Robustness check for the estimation of endogenous market concentration

1) Estimation using 2SLS:

Recall in section 5.2 we described the control function approach used to control for a potential bias arising from the endogeneity of *D* which is a binary variable. As indicated in Wooldridge (2015), this approach exploits the binary nature of endogenous variable but it is generally inconsistent if the probit model for the binary endogenous variable is mis-specified. This is in contrast with the robustness of the usual 2SLS estimator which does not use any distributional assumptions in the reduced form. If the probit model for the binary endogenous variable is correctly specified, then the control function procedure and 2SLS should give estimates that differ only due to sampling error. For this reason, we re-estimated equation (3) in section 3.2 using the 2SLS procedure and the results are shown in Table 4 (section 6) and Figure A3 below. The 2SLS results are very consistent with our results in Table 4 and Figure 5 in section 6 confirming the robustness of our results using the control function approach.

Figure A3. Predicted market concentration varying with regionalisation and the uptake of internet banking (using estimates from 2SLS in Table 4)



2) Estimation by adding additional instrument for B (branch density)

Table A4: Estimation results for national concentration in banking with and without additional instrument for branch density

Dependent variable: $\log\left(\frac{C_{it}}{100-C_{it}}\right)$	*With additional instrument for B* Estimated coefficients CF	Estimated coefficients 2SLS	*Without additional instrument for B* Estimated coefficients CF	Estimated coefficients 2SLS
t	0.089***	0.083***	0.090***	0.081***
	(0.0098)	(0.0105)	(0.0082)	(0.0113)
$\frac{1}{\ln S_{it}}$	61.512***	68.607***	49.706***	58.581***
	(6.6646)	(7.0343)	(7.4198)	(7.6082)
R_i	-5.858***	-5.025***	-11.674***	-8.038***
	(1.6776)	(1.5396)	(2.1856)	(1.7908)
B_{it}	0.124**	0.136***	0.286***	0.259***
	(0.0653)	(0.0506)	(0.0670)	(0.0688)
$R_i * \frac{1}{\ln S_{it}}$	68.643***	58.656***	149.774***	98.528***
	(22.7321)	(20.7393)	(30.1833)	(24.1566)
D	-2.395***	-1.739**	-2.058***	-1.368*
	(0.6092)	(0.7523)	(0.5838)	(0.8381)
*D*t*	-0.092***	-0.084***	-0.090***	-0.077***
	(0.0144)	(0.0138)	(0.0101)	(0.0144)
$D * \frac{1}{\ln S_{it}}$	36.481***	26.644***	31.362***	20.863***
	(6.7413)	(8.9247)	(6.4704)	(9.8031)
$D * R_i$	11.053***	9.442***	13.119***	7.686***
	(2.2500)	(2.0043)	(2.5263)	(2.4002)
$D * B_{it}$	-0.134**	-0.160***	-0.159***	-0.154**
	(0.0661)	(0.0527)	(0.0615)	(0.0700)

$D * R_i * \frac{1}{\ln S_{it}}$	-146.062***	-126.042***	-179.961***	-101.104***
	(32.4660)	(24.2483)	(36.7303)	(33.7451)
A (crisis)	8.492***	8.346***	9.572***	8.355***
	(2.4667)	(2.5152)	(2.0891)	(2.7722)
Constant	5.768	5.385	3.706	3.884
	(3.7189)	(3.9655)	(3.1020)	(4.0957)
$\hat{e}_{it}^{S}$	-13.997		-8.587	
	(17.5735)		(16.3207)	
$\hat{e}_{it}^{B}$	-0.493***		-0.981**	
	(0.1548)		(0.0883)	
$\hat{e}_{it}^{D}$	0.070		-0.128	
	(0.1351)		(0.0937)	
$\hat{e}_{it}^{R*S}$	-33.715		-199.214***	
	(40.2708)		(35.9062)	
Adjusted R^2	0.69	0.69	0.77	0.65
No of Obs.	430	430	430	430

Figure A4. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking with additional instrument for branch density: control function approach

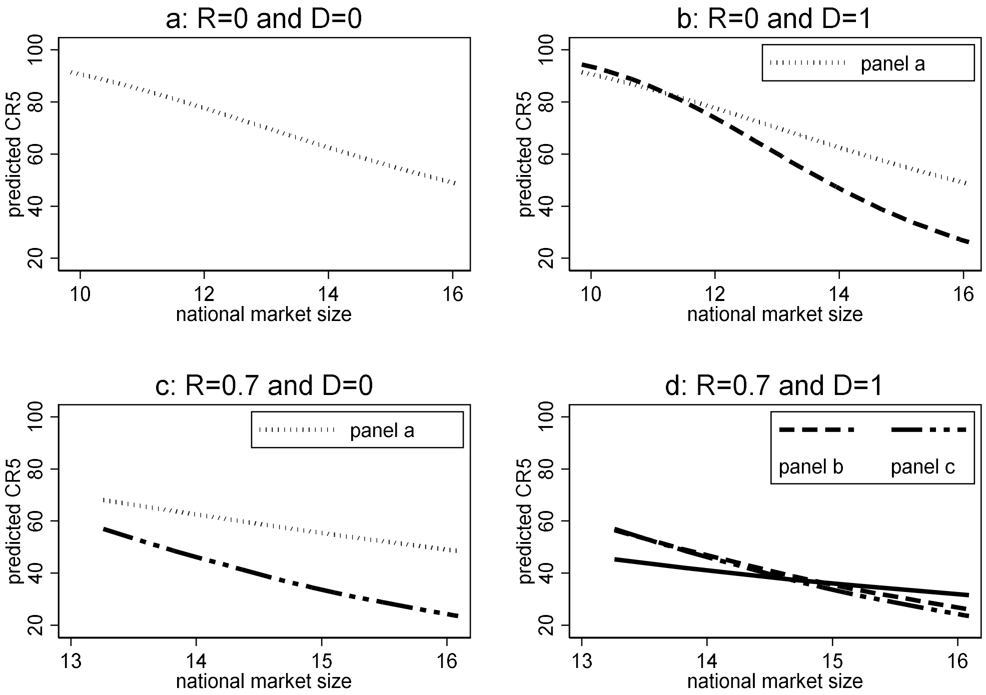
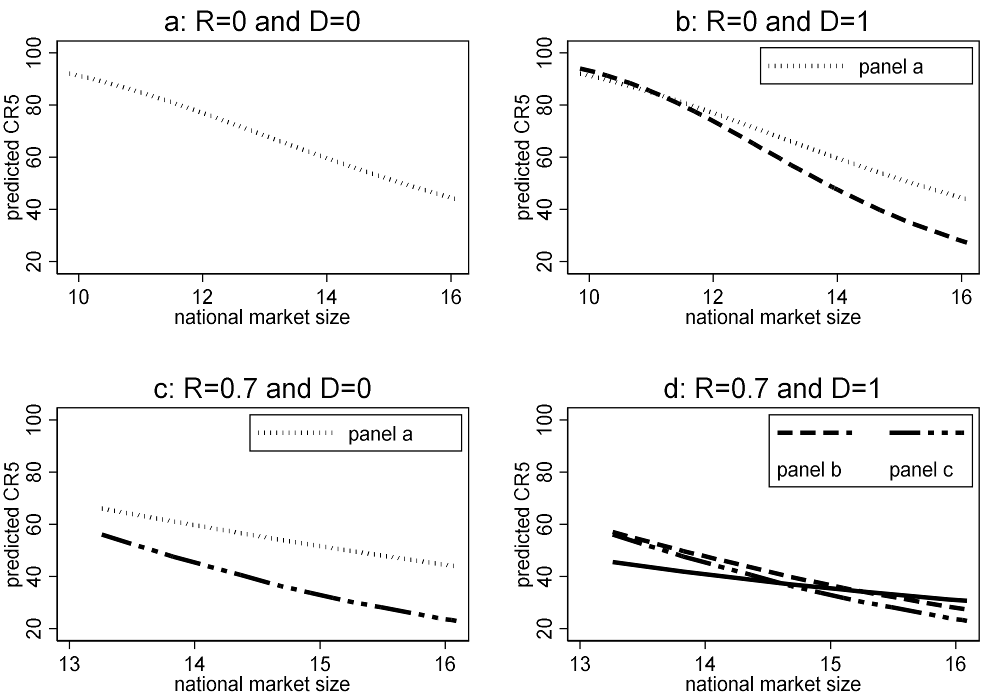


Figure A5. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking with additional instrument for branch density: 2SLS approach



3) Sensitivity analysis by excluding Luxembourg from our sample

We have already noted that Luxembourg might be an outlier in the concentration equation given its small population size and large total bank assets as measured by the ECB. If we exclude Luxembourg from the sample for estimating concentration, the results are reported in Table A5 and Figure A6 and A7. We have conducted F tests which confirm that the two specifications (with or without including Luxembourg as a potential outlier) in the table below are statistically different. However, the qualitative pattern described in section 6 has not changed.

Table A5: Estimation results for national concentration in banking: excluding Luxembourg

	With Luxembourg		*Without Luxembourg*	
Dependent variable: $\log\left(\frac{C_{it}}{100-C_{it}}\right)$	*Estimated coefficients CF*	*Estimated coefficients 2SLS*	*Estimated coefficients CF*	*Estimated coefficients 2SLS*
t	0.090***	0.081***	0.096***	0.113**
	(0.0082)	(0.0113)	(0.0078)	(0.0108)
$\frac{1}{\ln S_{it}}$	49.706***	58.581***	65.785***	70.333***
	(7.4198)	(7.6082)	(8.1423)	(7.2065)
R_i	-11.674***	-8.038***	-14.052***	-14.066***
	(2.1856)	(1.7908)	(1.7073)	(1.4633)
B_{it}	0.286***	0.259***	0.344***	0.368***
	(0.0670)	(0.0688)	(0.0712)	(0.0617)
$R_i * \frac{1}{\ln S_{it}}$	149.774***	98.528***	174.710***	168.517***
	(30.1833)	(24.1566)	(23.9657)	(19.1204)
D	-2.058***	-1.368*	-1.784***	-2.007***

	(0.5838)	(0.8381)	(0.5335)	(0.7054)
$D*t$	-0.090***	-0.077***	-0.084***	-0.089***
	(0.0101)	(0.0144)	(0.0102)	(0.0134)
$D*\frac{1}{\ln S_{it}}$	31.362***	20.863***	29.377***	33.711***
	(6.4704)	(9.8031)	(6.6548)	(8.0315)
$D*R_i$	13.119***	7.686***	12.272***	8.422***
	(2.5263)	(2.4002)	(2.0332)	(1.9204)
$D*B_{it}$	-0.159***	-0.154**	-0.078	-0.004
	(0.0615)	(0.0700)	(0.0664)	(0.0635)
$D*R_i*\frac{1}{\ln S_{it}}$	-179.961***	-101.104***	-164.155***	-105.115***
	(36.7303)	(33.7451)	(29.5933)	(26.9514)
A (crisis)	9.572***	8.355***	8.639***	6.994***
	(2.0891)	(2.7722)	(2.4853)	(2.8100)
Constant	3.706	3.884	-26.816***	-45.120***
	(3.1020)	(4.0957)	(3.8007)	(4.6722)
$\hat{e}_{it}^{S}$	-8.587		-64.828***	
	(16.3207)		(15.5927)	
$\hat{e}_{it}^{B}$	-0.981***		-0.897***	
	(0.0883)		(0.0842)	
$\hat{e}_{it}^{D}$	-0.128		0.099	
	(0.0937)		(0.1058)	
$\hat{e}_{it}^{R*S}$	-199.214****		-152.253***	
	(35.9062)		(41.0728)	
Adjusted R^2	0.77	0.65	0.79	0.72
No of Obs.	430	430	413	413

Notes: D is constructed using the threshold of IB at 25%.

Figure A6. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking without Luxembourg: Control Function approach from Table A5

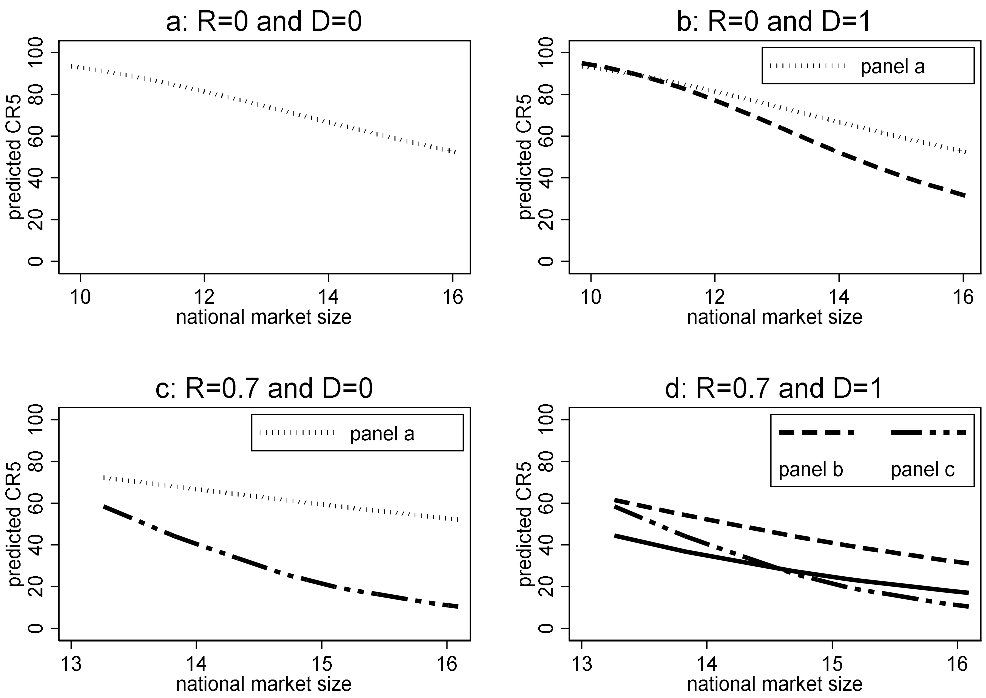
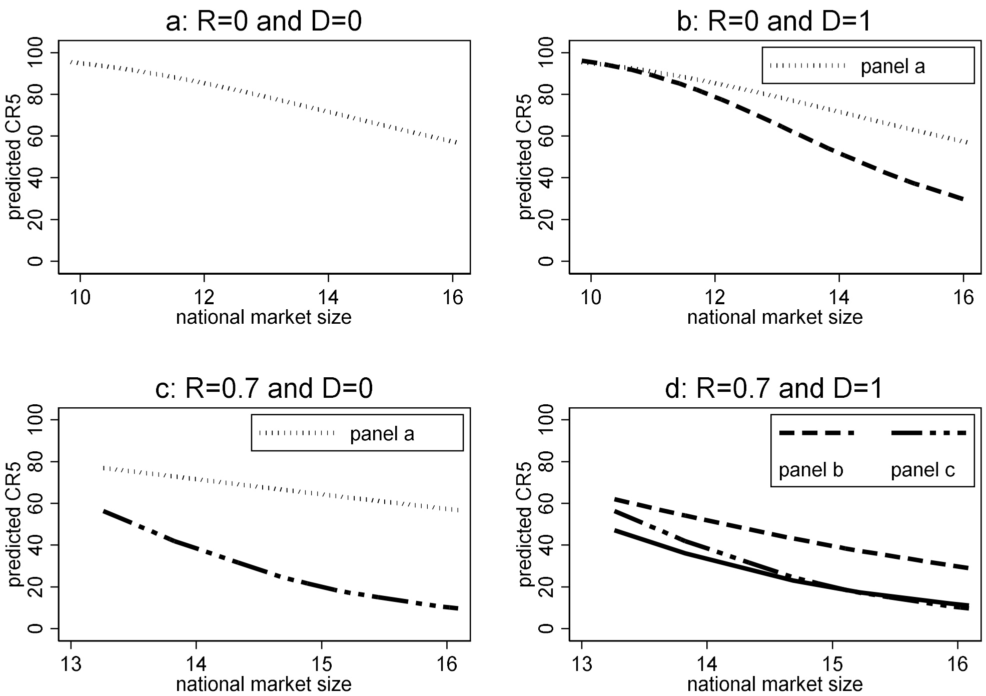


Figure A7. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking without Luxembourg : 2SLS approach from Table A5



4) Sensitivity analysis by using a different threshold value of *IB* for *D*:

We explored different threshold values for construction of the dummy variable *IB* used in the concentration estimations (equation (3)). Table A6 and Figures A8-11 report the results using a different cut-off point: D = 1 if IB > 30% and 0 otherwise. It is clear that the results are similar those reported in section 6 (Table 4 and Figure 5) , Table A5 and Figures A6 and A7 except that the control function for *D* becomes significant.

Table A6: Estimation results for national concentration in banking using a different threshold value of *IB* (30%) for *D*

	With Luxembourg		*Without Luxembourg*	
Dependent variable: $\log\left(\frac{C_{it}}{100-C_{it}}\right)$	*Estimated coefficients CF*	*Estimated coefficients 2SLS*	*Estimated coefficients CF*	*Estimated coefficients 2SLS*
t	0.088***	0.079***	0.096***	0.111***
	(0.0074)	(0.0097)	(0.0065)	(0.0088)
$\frac{1}{\ln S_{it}}$	47.640***	59.993***	63.717***	68.997***
	(8.4732)	(7.8319)	(8.7066)	(7.3570)
R_i	-11.905***	-7.536***	-14.337***	-14.918***
	(1.8549)	(1.8672)	(1.6527)	(1.5900)
B_{it}	0.334***	0.310***	0.392***	0.411***
	(0.0638)	(0.0752)	(0.0732)	(0.0651)
$R_i * \frac{1}{\ln S_{it}}$	151.265***	90.786***	177.250***	178.498***
	(24.9843)	(24.9911)	(21.8143)	(20.7751)
D	-2.274***	-1.433*	-2.020***	-2.395***
	(0.6167)	(0.8823)	(0.5393)	(0.7185)
*D*t*	-0.088***	-0.070***	-0.082***	-0.081***
	(0.0089)	(0.0138)	(0.0105)	(0.0133)
$D * \frac{1}{\ln S_{it}}$	31.313***	17.401***	29.311***	35.045***
	(7.3442)	(10.0909)	(6.2517)	(7.4821)
$D * R_i$	13.981***	7.340***	13.119***	9.374***
	(1.9327)	(2.8618)	(1.8877)	(2.2808)
$D * B_{it}$	-0.198***	-0.206***	-0.119*	-0.019
	(0.0725)	(0.0797)	(0.0684)	(0.0691)
$D * R_i * \frac{1}{\ln S_{it}}$	-191.799***	-96.623***	-175.481***	-117.358***
	(28.7854)	(41.1404)	(27.2524)	(32.8126)
A (crisis)	9.956****	8.151***	8.795***	6.637***
	(2.4685)	(2.6364)	(2.0525)	(2.3683)
Constant	3.416	3.790	-27.014***	-48.342***
	(3.6059)	(4.1917)	(4.3024)	(4.8895)
$\hat{e}_{it}^{S}$	0.323		-54.732***	
	(17.4236)		(17.1667)	
$\hat{e}_{it}^{B}$	-0.997***		-0.915***	
	(0.0809)		(0.0952)	
$\hat{e}_{it}^{D}$	-0.266***		0.211**	
	(0.0901)		(0.0991)	
$\hat{e}_{it}^{R*S}$	-211.504***		-162.920***	
	(39.3120)		(31.5484)	
Adjusted R^2	0.78	0.65	0.80	0.72
No of Obs.	430	430	413	413

Figure A8. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking with Luxembourg: Control Function approach from Table A6

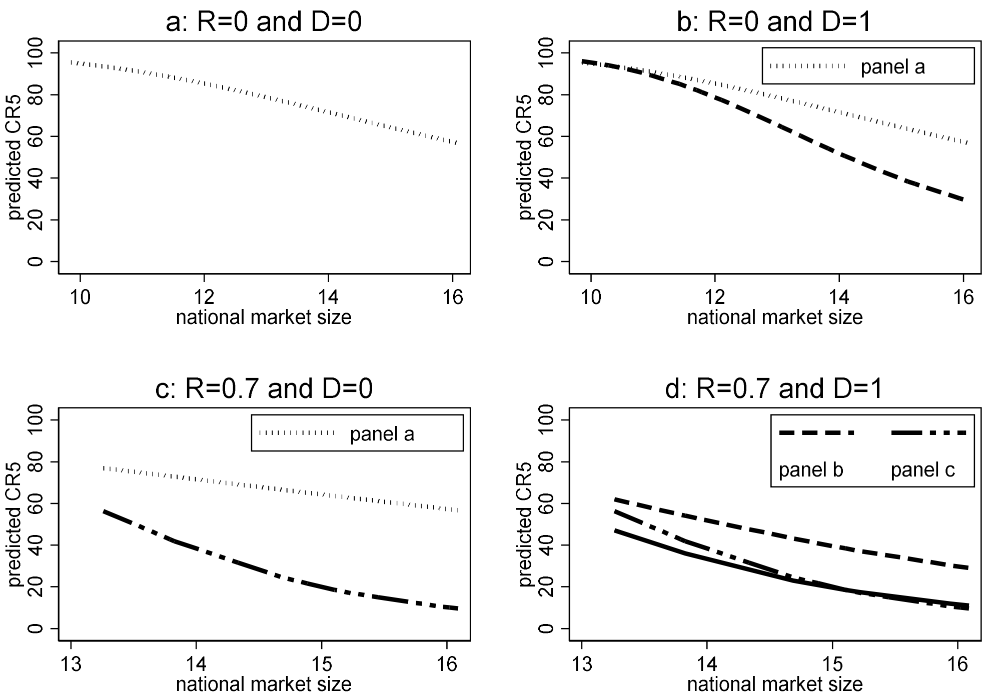


Figure A9. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking with Luxembourg: 2SLS approach from Table A6

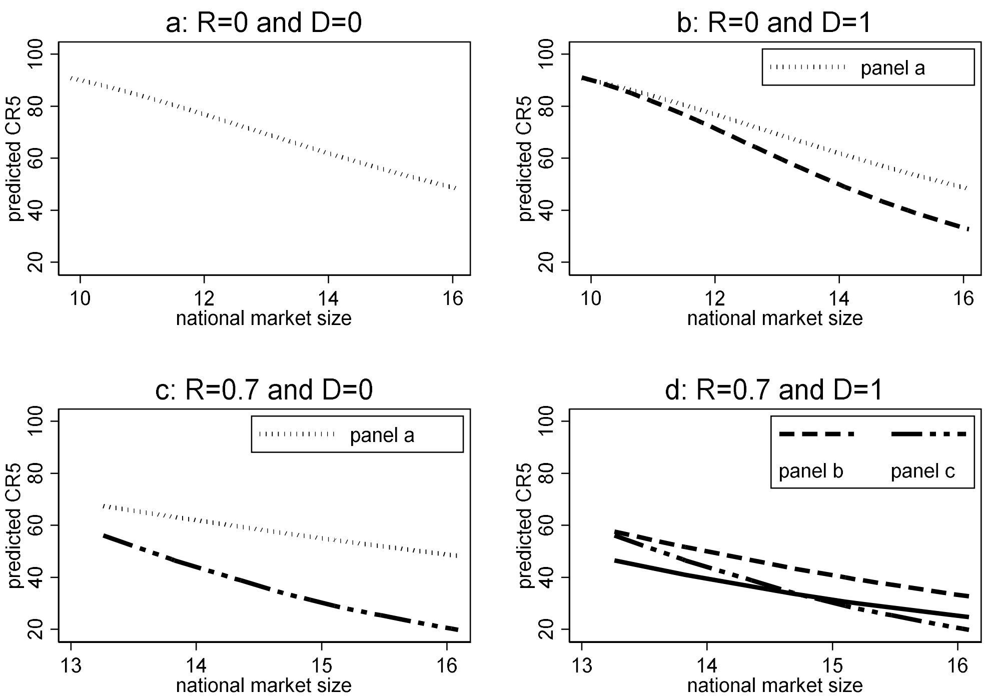


Figure A10. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking without Luxembourg: Control Function approach from Table A6

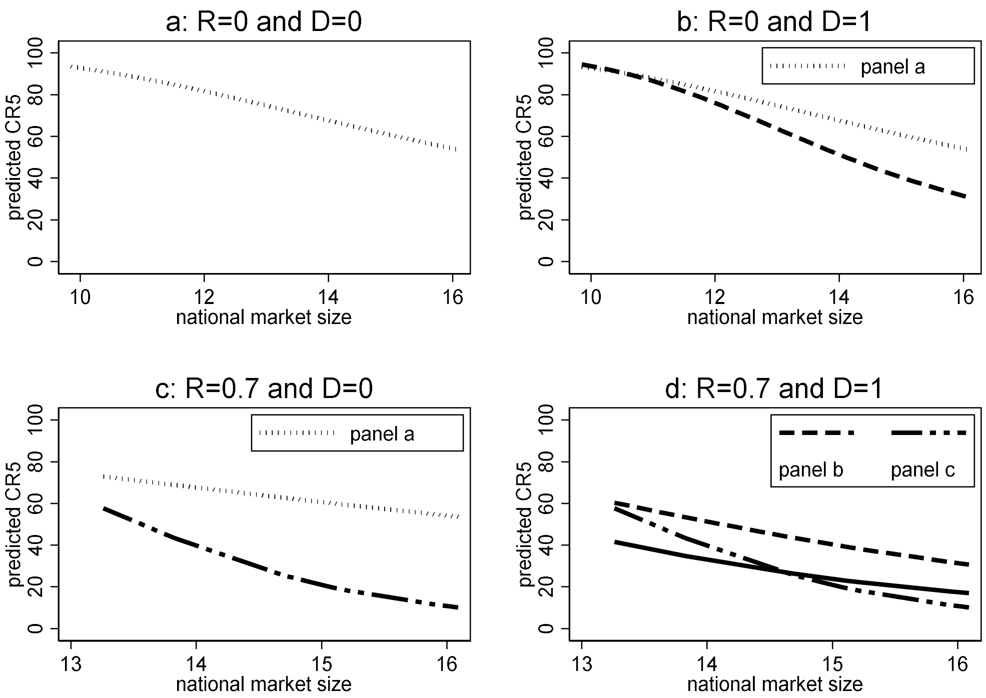
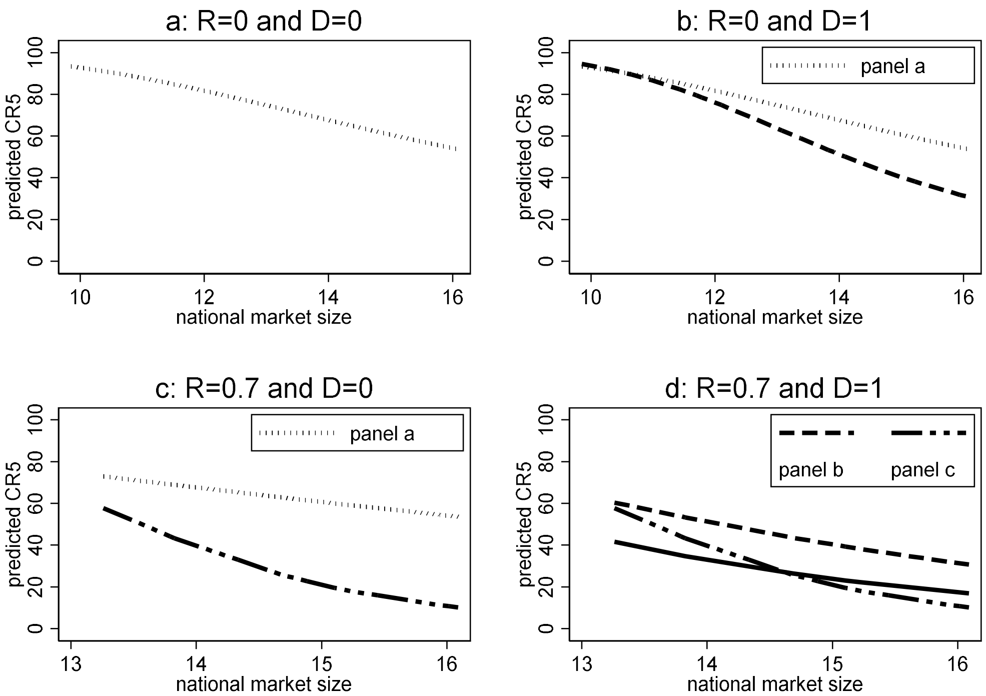
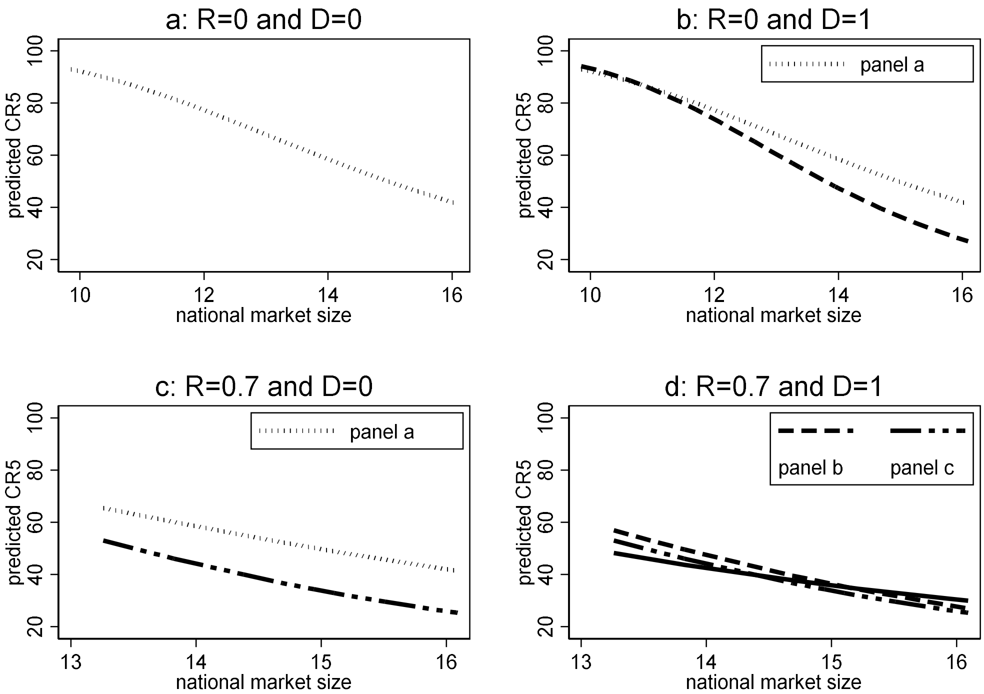


Figure A11. Predicted market concentration varying with different levels of regionalisation and maturity of internet banking without Luxembourg: 2SLS approach from Table A6




a: R=0 and D=0
b: R=0 and D=1
c: R=0.7 and D=0
d: R=0.7 and D=1
predicted CR5
national market size
panel a
panel b
panel c
20
40
60
80
100
10
12
14
16
13
15

Appendix 4: Sample Size Discussion

A panel of national data over a period relevant to the diffusion of an innovative product must inevitably be of limited sample size compared with, say, consumer level data. However, consumer (or firm) level data, even if was hypothetically available, would not be able to address our research questions. Our data sources and the nature of a diffusion process (which is fully completed by many countries within our sample period) mean that the size of the panel cannot be extended usefully in either the international or temporal dimensions. The question remains of whether our sample is inappropriately small. Calculating power for observed data provides no information beyond what the ordinary p-value (i.e. the probability of type I error) already provides (Hoenig and Heisey, 2001; Schulz and Grimes, 2005).

Nevertheless, to gain a greater feel for the possible limitations of our sample size, we have calculated the sample sizes necessary for 90% power in the following hypothetical cases:

To detect the size of the effect we have estimated based on our observed sample, what would be the sample size required to achieve the power of 90% at 1% significance level? More specifically, we calculated (using Stata) sample size required to detect the difference (at 1% significance level) in R-sq with and without our main covariates with the power of 90% for linear regressions. Our calculations suggest that to detect the differences in R-sq that are estimated in the current study, with a power of 90%, the sample size required for model 1 is 60 and for model 2 is 39.

We then calculated the minimum detectable effect given the number of main/control covariates and our sample size. Set power at 90% and significance level at 1% for linear regressions, the calculation shows that an average sample of our size could detect a minimum effect of the size indicated by r-sq difference of 0.009 for model 1 and 0.042 for model 2.

Table A7: Sample size analysis

	Our sample size	Number of main covariates	Number of full set of covariates	R-sq with main covariates	R-sq without main covariates	Detected effect of main covariates indicate by the difference in R-sq	Required sample size to detect the size of the effect of main covariates estimated by our sample (power at 90% and significance at 1%)	Minimum detectable difference in R-sq given our sample size (power at 90% and significance at 1%)
Model 1	381	9	23	0.9195	0.8638	0.056	60	0.009

Model 2	430	10	22	0.7710	0.3381	0.433	39	0.042

The above calculations suggest our significance tests are unlikely to be underpowered. However, these calculations don't completely answer the question "would the average hypothetical dataset of this size contain enough evidence to reject H_0?" because a different sample may detect the effect of main covariates at a different magnitude. Given the limited data sample we have, our findings should be interpreted with the appropriate caution.