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Mortgage lending through a fintech web platform. The roles of competition, diversification, and automation☆

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A B S T R A C T

How do banks offer and price mortgages when an online platform enables them to reach regions where they have no branches? With unique data on responses from differently located banks to each applying household and a shift-share instrument for market concentration, we find banks to make more and cheaper offers to more concentrated local markets. We rationalize this as investments in lucrative market shares given customer switching costs. Banks also improve their inter-regional portfolio diversification with more attractive offers to regions more complementary to their home locales. Finally, banks` choices become increasingly automated, reducing their operating costs.

1. Introduction

We analyze how banks choose offer propensity and pricing in response to mortgage applications when a Swiss online platform, together with hedonic models of collateral appraisal, allows them to make offers to clients from across the country. This includes cantons (states) where the bank lacks branches, reputation, staff, or local expertise. We exploit unique data on responses from different banks to each application. Further, we obtain exogenous variation in each canton`s prior mortgage market concentration by exploiting that Switzerland's largest two banks at the time, UBS and Credit Suisse (CS), had to reduce domestic mortgage lending following their losses in the US subprime crisis. This reduced market concentration in cantonal markets, the higher a canton's *prior* Big Two share.

Confronted with the FinTech opportunity to replace Big Two lending in whichever canton they find most attractive, we find banks to offer more often and at lower margins to more rather than to less concentrated cantons. We rule out diversification considerations as a driver and argue adverse selection concerns to be unlikely. Instead we rationalize this behavior as investments into more lucrative future market shares

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given switching costs, see Klemperer (1995). While potential clients shop around for mortgages, where much is at stake and prices are comparable, we explain that they are often forced to refinance with the same bank so that refinancing is often an *add-on* to their initial mortgage. Further, after onboarding new mortgage clients, banks can often *cross-sell* other banking services such as payment accounts or credit cards, for which prices are harder to compare. And banks can exploit clients' resulting stickiness more in more concentrated cantons.

In addition to analyzing bank responses to exogenous variation in prior market concentration, we also analyze responses to opportunities to increase the geographic diversification of their mortgage portfolios. Accounting for both observed and unobserved variation in borrower and lender heterogeneity (with borrower and lender fixed effects), we find that banks make more and lower-margin offers in response to mortgage applications from cantons where the proxies for the probability of default (PD), i.e., the unemployment rate, or the loss given default (LGD), i.e., the house price change, exhibit a lower correlation with those in the bank's headquarter canton.

Finally, we analyze the extent to which banks automate their offer and pricing decisions. Decisions are found to stick closer to rules when applicants appear safer, when banks are larger or more mortgage-specialized, and the more experience banks have already accumulated online. So more online experience allows to lower operating costs.

The data we analyze have three major advantages over existing information sets. First, we can observe how banks choose to engage clients when freed of historical legacies of geography. Second, we observe both mortgage applications pre-intermediation and subsequent lender responses. So, we can distinguish demand and supply in a way not possible with data on completed contracts. Third, we observe for each application not just the response from one, but from several different banks. This allows us to analyze how *different* banks respond to the *same* borrower and so account for any endogenous matching of different types of borrowers to different types of lenders. If we observed only completed contracts, banks from other cantons might have attracted only low-risk (along unobservable dimensions we cannot control for) clients keener to contact also lesser-known banks to exploit their good creditworthiness, or they might have attracted only high-risk clients who failed to get a good offer from local banks. On the platform by contrast, each household gets responses both from more local and from more distant banks, so we can directly compare responses within the same client. Following pioneering work by Khwaja and Mian (2008), the methodology of analyzing lending variation both within each lender and within each borrower has by now been applied by many papers on bank lending to firms with more than one bank relationship, including Jiménez et al. (2012) and Chodorow-Reich (2014). It is less common for researchers to observe relationships with different banks for the same household. Hence such identification has, to our knowledge, been achieved for lending to households only by Basten (2020) with the same data, and by Michelangeli and Sette (2016) with simulated applications to different banks.

The identification strategy for our main analysis exploits changes in local concentration caused by overseas (US subprime) losses of Switzerland's Big Two banks at the time. As a result of these losses, they had to cut domestic mortgage lending growth to rates significantly short of those of the market. We exploit each year's shortfall of Big Two relative to market-wide lending growth as an exogenous shift, and map its impact to Switzerland's 26 cantons based on the Big Two's *prior* market share in each canton. Importantly, we exploit only that part of the Big Two lending reduction in each canton which is explained by prior market shares, not endogenous choices to reduce lending more in some cantons than in others. The product of shift and shares yields a shift-share or Bartik style instrument. Exploiting prior variation in exposure to exogenous supply shifts, as previously done in banking by Mian and Sufi (2012), Chodorow-Reich (2014) or Gete and Reher (2018), is particularly clean in our setup as US losses of UBS and CS are quite exogenous to later online bids of small Swiss banks with no noteworthy US exposure. In particular, neither of the Big Two participated in the platform we analyze: They already had branches everywhere and presumably did not need to use the platform.

Our key results, more and lower-margin offers sent to more concentrated markets, are apparent in simple descriptive plots of offer behavior against market concentration, but the *causal* effects of prior market concentration are larger than descriptive correlations. For *unobservable* attractiveness of some markets has arguably increased the number of offline providers and so *reduced* prior market concentration while also *increasing* the frequency and attractiveness of current online offers.

These results are robust to a wide range of variations in our methodology. First, we control for either both household and bank characteristics, household characteristics and bank fixed effects, or household group fixed effects and bank fixed effects. Second, we combine analyses on prior market concentration with analyses on the potential for each local market to improve geographical portfolio diversification and find either driver robust to the other. Third, another variation computes standard errors as recently recommended by Adão et al. (2019) for Bartik instruments. This addresses potential concerns about a limited number of shifts in the shift-share design. Fourth, results are robust also to controlling for plausible correlates of prior market shares.

2. Contributions to the existing literature

Our findings on how online pricing of mortgages relates to local competition extends to the financial sector an emerging literature on how the internet changes competition pioneered by, amongst others, Cavallo (2017) and Gorodnichenko et al. (2018). They relate also more specifically to the active recent literature on the effects of new financial technology or FinTech. We refer to Thakor (2020) who defines FinTech as "the use of technology to provide new and improved financial services".[1] Of the four uses of this technology listed by Thakor, our paper focuses on the lowering of search costs when matching transacting parties. Our setup also fits well with the more recent alternative definition of FinTech by Allen et al. (2020) as brokerage rather than dealership, i.e., of lending without taking the loans onto the own balance sheet. By contrast, Buchak et al. (2018) consider only FinTechs simultaneously defined as shadow banks in the sense of non-depository institutions. We focus on the activity rather than on who carries it out, as the type of online platform we study may be organized by a non-bank as in our case, or may be taken over by a bank and yet have much the same effects.[2] Finally, Fuster et al. (2019) recently emphasize that FinTechs can address market frictions. Consistent with this, we show the online platform studied to specifically address frictions from geography. It gives borrowers access to more possible lenders, which bears analogies with recent findings in Bartlett et al. (2022) on how FinTech has improved access to mortgages for minority groups.[3]

Concerning more specifically banks' response to prior market

[1] This is consistent with the definition by the Basel Committee on Banking Supervision as "technologically enabled financial innovation that could result in new business models, applications, *processes*, or products".

[2] In the years studied Comparis as a non-bank provided a web mortgage platform in Switzerland, while more recently Goldman Sachs as a foreign bank became interested in becoming involved, and the Swiss bank UBS also considered organizing a platform without taking all mortgages originated there on its own balance sheet. See https://nzzas.nzz.ch/wirtschaft/goldman-sachs-prueft-einstieg-in-schweizer-hypothekarmarkt-ld.1428046?reduced=true and https://www.ubs.com/microsites/impulse/ de/digital/2019/mortgage-platforms.html, last accessed in April 2021.

[3] Beyond allowing in particular borrowers from more concentrated local markets to get more and better offers, and allowing lenders to better diversify their portfolio and lower operational costs, mortgage contracting through a web platform also has the benefit of being possible also during pandemics like COVID.

concentration, we are confronted with a setup that lends itself to *multi-product pricing* as defined in amongst others Tirole (1988) as a setup in which the pricing of one product affects not only the quantity of that product bought but also the quantity of other products. Behavior in such a setup can also be rationalized by provider switching costs as explained in Klemperer (1995). More concretely, we explain that many clients are forced to renew their mortgage with the same lender after a maximum of ten years, in which case the lender can practically dictate the rate. Hence lenders can do *add-on pricing* as characterized by Ellison (2005) and Gabaix and Laibson (2006) and applied to mortgage lending by Agarwal et al. (2017).

Going beyond the role of prior competition, we study also how bank decisions depend on the potential to geographically diversify their mortgage portfolio other than through securitization or bank holding companies, both of which the financial crisis showed to be burdened by agency problems.[45] We thereby complement a by now extensive literature that exploits the US interstate bank deregulation following Jayaratne and Strahan (1998), as evidenced by Goetz et al. (2013) and Goetz et al. (2016), and references therein. While Goetz et al. (2013) find increases in regional diversification to have reduced average stock market valuations of US bank holding companies, Goetz et al. (2016) find that it did nonetheless overall *reduce bank riskiness* (as measured by the standard deviation of bank stock returns as well as the Z-score and other risk measures). They argue that the hedging of idiosyncratic local risks dominated potential reductions in banks' ability to monitor loans located at a larger distance. While their risk measures cover banks' entire balance sheets, including loans to firms and other assets, we focus on how banks can better diversify specifically their mortgage portfolios. Through an online platform like the one studied here, lending decisions for different regions can still be made by the same central decision-maker, removing the agency problems between bank headquarters and local credit officers traditionally associated with larger distance. The online platform analyzed may thus reduce agency costs even beyond the level analyzed by Berger and DeYoung (2006), who found reductions in distance-related agency costs within US bank holding companies through improvements in information processing and telecommunication.[67]

The role of these risk management relevant factors survives also when we control for various measures of distance between potential borrower and lender. This suggests that behavior which can be interpreted as improving banks' portfolio diversification, is not just driven by banks' striving to earn bigger margins in return for offering borrowers a nearer branch to bank at as in the Degryse and Ongena (2005) analysis of Belgian corporate loan pricing. In fact, on top of the effects of PD and LGD complementarity between borrower and lender canton, we also do find banks to charge lower prices offered to more distant borrowers. However, while those effects are statistically significant, their size is relatively small when we control for portfolio complementarity in addition to using both borrower and lender fixed effects. We rationalize this by observing that the changes in lender technology already noted by Petersen and Rajan (2002) for corporate lending are likely to apply even more to online mortgage lending.

Finally, after having estimated how banks' offer and pricing decisions depend on market concentration, portfolio complementarity and other household and bank characteristics, we estimate a regression model with multiplicative heteroscedasticity as pioneered by Harvey (1976) to explore which bank responses are more automated. We find less discretion for safer applications, as well as by larger or more mortgage-focused banks. We also find discretion to decrease with the number of online responses a bank has already sent out, allowing to reduce operational costs and use the available hard information more efficiently, see also, e.g., Berg et al. (2020). We so bring together the literature on rules vs discretion in banking (Cerqueiro et al., 2010) with the recent work on how the web changes pricing.

3. Data and institutional background

3.1. The online platform

The key data used for our investigation stem from the Swiss website *Comparis.ch.* Between 2008 and 2013, they operated a platform on which households could apply for mortgages and were then provided responses from several different banks.[8] Importantly, there was no human broker intermediating between applicants and suppliers. This changed from 2013 when Comparis acquired human broker firm Hypoplus, but no human broker was involved during our sample period.[9] For reasons of data quality and for our IV strategy, we focus on 2010–13. The resulting data are unique and offer at least five advantages for our analysis. First, we separately observe demand and supply.[10] Second, banks in their operation and we in analyzing them can rule out differential access to clients from different regions based on, amongst others, pre-existing branch networks. Third, we can rule out that different banks tend to interact with different types of clients. Fourth, we observe 100 % of the information each bank also has on each client. Bank decisions cannot be biased by the use of soft information acquired through prior personal interaction. Furthermore, as banks do not learn applicants' names, they must rely on the information we fully observe and cannot complement it e.g. with external credit scores. Fifth, in contrast to many brokers who earn differential fees from different lenders as studied in Robles-Garcia (2019), the platform analyzed was paid by borrowers only.

While the volume of mortgages issued through the platform was still limited relative to that of the offline market, bank behavior online was representative to that of banks' entire balance sheets: For example, we

[4] A step in between lending through bank branches and lending through online platforms is of course the use of brokers, as discussed and analyzed for the UK in Click or tap here to enter text.Robles-Garcia (2019)Click or tap here to enter text.. She also points out that 33% of mortgage lending in the US (44% before the crisis) and about 50% in the UK, Australia and Canada are conducted through brokers. But she shows that brokers may prefer to intermediate those mortgages for which they receive the highest bank commissions, whereas the platform analyzed here receives money from borrowers only and hence remains neutral. For our analysis we hence observe banks' true responses, unfiltered by potentially interested brokers.

[5] Swiss banks refinance part of their mortgages through covered bonds. But bonds plus covered bonds account for less than 10% of their liabilities, compared to about 70% for deposits. Further, any mortgage used as collateral for a covered bond remains entirely on the bank balance sheet.

[6] Beyond allowing lenders to match with potential borrowers in regions where lenders have no branch network, as studied in this paper, a web platform may also allow lenders to access borrowers who even within the region of their branch network may not have talked to that bank due to perceiving the bank as catering only to different types of customers. So, our estimates if anything under-estimate the potential for new borrower lender matchings.

[7] More recently, Berger et al. (forthcoming) and Berger et al. (2020), using client bank branch distance as an instrument for the existence of a prior relationship, find prior relationships to affect lending terms during the pandemic for households and businesses, respectively.

[8] The Online Appendix examines how representative borrowers and lenders on the platform are.

[9] See https://www.hypoplus.ch/fr/hypotheken-news/item/in-eigener-sache/comparis-erhaelt-mit-hypoplus-eine-schwesterfir ma-fuer-beratung.html in German or https://www.lenzstaehelin.com/en/news-events/deals-cases/comparisch-acquires-hypo plus-ag in English, both accessed in April 2021. Checks show that observations from 2013 were not contaminated by this and omitting 2013 yields qualitatively the same results.

[10] Two other recent papers seek to capture supply, in their case of credit card lending, by use of unsolicited credit card mail offerings, so as to investigate how this supply is affected by consumer protection regulation (Han, Keys, and Li, 2018)) and the opioid pandemic (Agarwal et al., 2022)) respectively.

see that in the period studied Big 2 market shares including offline business fell in 25 of 26 cantons. This is in line with results in Basten (2020) who finds that banks' online mortgage pricing (observed in the same online dataset) responds to higher capital requirements, and that banks' mortgage volume growth (gleaned from banks` annual balance sheets) adjusted correspondingly.

Observations on how different banks respond to the same client have to the best of our knowledge until recently been achieved only in research on lending to corporates. In contrast, households engaged in mortgage borrowing have not been observed to interact with several different banks. Yet Jordà et al. (2016) and other papers have shown forcefully the importance of mortgage markets in banking, financial and general economic crises, given that mortgages tend to be the largest financial liability of most households as well as the largest class of assets for many banks. And endogenous matching is likely to matter also for our questions of interest, because offline the type of households willing to contract with distant banks may differ from the type who stay with local banks only. To our knowledge the first paper to observe how different banks respond to the same mortgage borrower is Basten (2020) who uses the same data as we do here to analyse how banks have responded to Basel III counter-cyclical capital requirements.

For the present purpose, the data include two outcomes of interest. First, an indicator of whether a specific bank makes an offer to a specific client. Second, given that it does, the rate offered.[11] Offers can consist of between 1 and 3 tranches of different amounts, which may differ in the rate fixation period as well as in the offered interest rate. For each tranche, we subtract from the offered mortgage rate the swap rate for the same fixation period applicable on the day of the offer, as available through Bloomberg. This is to reflect the bank's refinancing costs absent any maturity transformation and is the measure of refinancing costs commonly used in the market under study, see also Basten (2020) and Basten and Mariathasan (2023). Finally, we compute the weighted average across the up to three tranches, with weights given by the fractions of the total mortgage amount attributable to the respective tranche.[12] Prices offered here are indeed a key dimension along which banks can influence how many mortgage contracts they conclude each period. Thus Basten (2020) shows, using the same data, how banks more affected by higher capital requirements increase offered rates more and thereafter end up with lower growth rates in their mortgage volumes. Important to emphasize when we analyse how offers are related to amongst others local market concentration is the fact that in Switzerland banks can and do offer customer-specific rates, as in the US or Germany and unlike for example in the UK where Robles-Garcia (2019) reports banks to offer the same rate to every customer with the same fixation period and LTV. Also worth mentioning is that non-banks allowed to offer mortgages, including insurers and pension funds, have until now been regulated no less strictly than banks and so their combined market share has never significantly exceeded 5 %.

Offers were binding conditional on subsequent verification of information provided on applicant income and wealth. Unfortunately, we do not observe which offer is accepted, as this happens on hard paper rather than on the platform, but offers received through the platform typically outperform offline offers so that a high offer acceptance rate seems likely. At the same time, we emphasize that to this point a recent study estimated platform lending to account for only 3.7 % of market wide lending,[13] so platform behavior so far has not significantly changed the market overall. Rather, as the benefits of the platform to lenders and borrowers have meanwhile motivated more and bigger banks and non-banks to participate in or even operate their own platforms, we deem our analysis to show how platforms *can* change lending markets, not as a case of how this platform *has* changed the market overall.[14]

As we know each bank's name, we complement the Comparis data with data from banks' annual reports on their total assets, mortgages over total assets, deposits over total assets, and capitalization. We also add data on actual house price growth by region from Fahrländer Partner Real Estate (FPRE). Together with Wüest & Partner and IAZI, FPRE is the leading Swiss real estate consulting company who, amongst other services, provides hedonic models that allow banks to gauge whether the market price a mortgage borrower wishes to pay is deemed appropriate. Using the same hedonic quality adjustments they also compute house price indices for different quality segments from which we compute house price growth. Finally, to construct our instrument we use public data on the Big Two market shares.

3.2. Descriptive statistics

Overall, we start with 6914 applications, which attract a total of 25,125 responses. 20,583 of these are offers and 4542 rejections. Table 1 shows the corresponding Summary Statistics. To provide a picture that corresponds as closely as possible to the data used for the subsequent regressions, the summary statistics use the same number of observations as the regressions. Thus Panel (A), which focuses on the key characteristics of the mortgage applications, assigns more weight to applications that received more responses. The number of responses varies between 1 (in 1.53 % of cases) and 10 (in 0.04 % of cases). Most applications received between 3 and 6 responses, the average application about 4 responses. The mortgage amount applied for, and which by design could not be adjusted by the responding banks, varied between CHF 100,000 and CHF 2000,000, with an average value of a bit under 600,000. The loan-to-value (LTV) ratio varied between 15 % and 90 %, with an average value of about 65 %. The maximum is shaped by the fact that for any mortgage violating the self-regulatory requirement of at least 10 % of "hard equity" (excluding pension wealth) from the household, the bank willing to provide it would have faced a regulatory risk weight of 100 % instead of on average about 40 %. The loan-to-income (LTI) ratio varied between 0.69 and 9.62, with a mean of 3.59. Household income varied between CHF 48,000 and 600,000, with a mean close to CHF 170,000, wealth including pension fund wealth reached an average close to CHF 500,000. Mean age was 46.

Next, Panel (B) gives the key regional characteristics. The Herfindahl-Hirschmann Index (HHI), i.e. the sum of squared shares in cantonal mortgage markets, concentration ranges across the 26 cantons between 0.12 and 0.49, with a mean of 0.18 and a standard deviation of 0.05. The shift or excess lending of the Big Two relative to the whole market at the national level varied was as low as −3.4 in 2010 and −2.4 in 2011, turned to 0.16 in 2012, but was again negative at −1.75 in 2013. The exact timing depended on the lags with which the extents of US losses of the Big Two became known, plausibly exogenous both to later online bids of Swiss local banks, and to potential unobserved

[11] We do not observe every bank responding to every application. The platform providers revealed that banks pre-filtered on some applicant characteristics but did not reveal which ones. Therefore, in a variation we filled in all non-responses and coded them as rejections, but this did not materially change our results.

[12] As most offers have only one tranche, focusing on the first tranche only, rather than on weighted averages across all tranches, yields qualitatively the same results.

[13] https://blog.hslu.ch/retailbanking/2021/05/17/der-online-hypothekarmarkt-schweiz-ist-auch-2020-weiter-gewachsen/

[14] Despite its benefits, the platform in the form analyzed here has meanwhile left the market. Studying platforms that have replaced it seems to suggest that users may missed some human advice (which other new platforms are now offering) and that the platform itself earned too little from borrower fees alone.

Table 1
Descriptive statistics.

	N	Mean	SD	Min	Max
(A) Applicant Characteristics					
Year	25,125	2011	1	2010	2013
Month	25,125	6	3	1	12
Mortgage Amount in CHF	25,125	566,274	332,695	100,000	2000,000
I(New Mortg.=1)	25,125	0.540	0.500	0.000	1.000
Loan-to-Value (LTV)	25,125	64.500	17.300	15.000	90.000
I (LTV > 67 %)	25,125	0.530	0.500	0.000	1.000
I (LTV > 80 %)	25,125	0.080	0.260	0.000	1.000
Loan-to-Income (LTI)	25,125	3.590	1.520	0.690	9.620
I (LTI > 4.5)	25,125	0.230	0.420	0.000	1.000
I (LTI > 5.5)	25,125	0.080	0.270	0.000	1.000
Household Total Income	25,125	167,603	88,961	48,000	600,000
Household Wealth incl. Pension Fund	25,125	469,333	515,877	10,000	3180,000
Applicant Age	25,125	46	10	28	73
(B) Regional Characteristics					
Herfindahl-Hirschmann Index (HHI)	25,125	0.180	0.050	0.120	0.490
Shift	25,125	−2.072	1.374	−3.425	0.164
Big Two Cantonal Mortgage Share 2009 in%	25,125	0.307	0.085	0.091	0.569
Shift*Share	25,125	−0.636	0.472	−1.949	0.093
Multi-Market Contact (MMC) Index	25,125	0.070	0.030	0.050	0.400
Number of Online Providers (NOP)	25,125	10.920	2.520	4.000	14.000
Single-Family Home Price Growth	25,125	4.070	4.070	−3.990	15.270
(C) Bank Characteristics					
Bank Total Assets (TA)	25,125	16,932	12,841	434	37,804
Mortgages/TA	25,125	69.820	10.430	39.790	90.620
Deposits/TA	25,125	47.800	17.900	16.720	65.630
Capital Ratio	25,125	7.250	1.030	4.720	11.330
(D) Interaction Characteristics					
Experience in 1000 Web Responses	25,125	4.073	2.939	0.001	10.153
Correlation of Unempl. Rates 1973–2019	25,125	0.920	0.660	0.680	1.000
House price growth correlation	25,125	0.770	0.190	0.150	1.000
Branch Distance in km	25,544	20.861	24.970	0.000	174.798
Responses per Application	25,125	4.240	1.450	1.000	10.000
Response Time in Hours	25,125	97.410	151.720	−2.730	789.100
I (Offer = 1)	25,125	0.820	0.380	0.000	1.000
Weighted Spread Offered	20,583	0.900	0.210	0.490	1.520

Panel (A) shows applicant characteristics for all responses sent in 2010–2013, so the weight of each application corresponds to the number of responses included in our regressions. The new mortgage indicator marks mortgage applications when the object is first bought rather than refinanced. (B) shows relevant characteristics of the region where the collateral is based. The NOP, HHI and MMC measures of competition vary across the 26 cantons. Refer to Section 3.1 for details. (C) shows key bank characteristics. (D) shows key response characteristics. Unemployment and house price change correlation measure the correlation between the applicant's and the bank's canton. Weighted Spread is the amount-weighted average across the 1–3 tranches offered, where spread is the rate offered less the swap rate for the corresponding maturity.

relative attractiveness of lending to different cantons.[15] We map these shifts into the 26 cantons based on prior Big Two market shares of between 9 % and 57 %, yielding a shift*share instrument of between −2 and +0.1 percentage points (pp). The multi-market contact (competition) measure (MMC) of how many competitors in a canton a bank meets on average in how many other cantons ranges between 0.05 and 0.40 with an average of 0.07, while the number of online providers varies across cantons between 4 and 14 and averages 11. Finally, we see that house price growth varies between −4 % and +15 % with a mean of close to 4 %.

Looking at the characteristics of the 26 participating banks in Panel (C), where banks are again weighted by the number of responses sent out, total assets (TA) range between CHF 434 million and CHF 37.8 billion, with an average of 16.9 billion. These numbers reflect that the platform did not feature any of the banks with a nation-wide branch network such as UBS and CS, given that UBS' total assets in 2010 were about CHF 1.3 trillion and those of CS about CHF 1 trillion. Rather the platform was used primarily by so far more local banks who could benefit from reaching new regions through the platform. Between about 40 % and 91 % of these assets, and on average 70 % of them are invested in mortgages, which reflects the general focus of Swiss retail banks, see also Basten (2020). On the liability side, the most important position for most banks are deposits, ranging between about 17 % and 66 % and averaging 48 %. The unweighted capital ratio ranged between 4.72 % and 11.33 % and averaged 7.25 %.

Panel (D) finally gives the key characteristics of bank-household interactions. First, when sending out responses, banks could draw on experience with between 0 and about 10′000 prior responses, with an average of about 4′000. Relevant for portfolio diversification, the inter-cantonal correlation of unemployment rates was on average 92 %, but goes as low as 66 % and has a high SD of about 68 %. This reflects some remaining potential to lower correlations in the portfolio. The inter-cantonal correlation of house price changes achieves a mean of 77 % with a SD of 19 %, but which goes as low as 15 %. This reflects the fact that while real estate markets in all cantons are affected by the same interest rate, net immigration differs considerably due to different languages and so different source country compositions, as does regional economic specialization. The applying household was located between 0 and 175 km and on average about 21 km from the responding bank's nearest branch, both known to the level of about 4′400 zip codes. We focus on geodesic distance, but note that Geographic Information System (GIS) based driving distances or times available for a subsample yield very similar results. Applications received between 1 and 10 and on average a bit over 4 responses, which took about 97 h or about 4 days. About 82 % of all responses are offers, which are personal and binding conditional on the verification of the supplied information. The average rate offered amounts to 2.16 %, implying a mean spread above the swap rate for the same period of 90 basis points (bps). After this discussion of descriptive statistics, we refer to ***Appendix Tables 9–11***, which show the sample to be largely representative of the total mortgage market.

4. Responses to market concentration

4.1. Hypothesis on local market concentration

Our main interest is in how banks' online offer behavior responds to how concentrated the mortgage market in the applicant's region has been so far. In the basic oligopolistic version of the well-known Monti-Klein model as summarized e.g. in Freixas and Rochet (2008) banks optimize lending and deposit business separately, then lend or borrow any difference between loan and deposit volumes in the interbank market. Further, they do so for a single period only. Then we expect banks to demand *higher* prices the *more* concentrated the market is.

But on the other hand, and potentially more realistically, clients in retail banking buy packages of services from the same bank including several components of mortgage loans, mortgage loan refinancing, deposit accounts, transaction accounts, or investment advice. This allows banks to ***cross-sell*** products. Thus Basten and Juelsrud (2023) show in the very similar Norwegian setup that for example an existing deposit

[15] Results are qualitatively confirmed if we use as shift only Big Two growth without subtracting market-wide growth as control for mortgage demand. Our baseline subtracts market-wide growth to facilitate interpretation.

account makes a household about 20pp more likely to also borrow from the same bank after controlling for rates at that bank and at all potential competitors, thereby showing explicitly the high empirical relevance of cross-selling. One key reason why customers do not shop around afresh for each banking service are ***switching costs***, see Beggs and Klemperer (1992), Sharpe (1990), Rajan (1992), Klemperer (1995) or Thadden (2004).

Sharpe (1990) points out that a setup with switching costs "drives banks to lend to new [borrowers] … at interest rates which initially generate expected losses", expecting later markup increases to make this worthwhile. Relatedly, Tirole (1988) points out that firms may choose to price one product at lower or even negative margins if they expect this to pay off by selling more of a sufficiently lucrative ***complement***.[16] A similar intuition applies to the pricing of "***add-ons***" intricately linked to the "base good". First characterized by Ellison (2005) and Gabaix and Laibson (2006), Agarwal, Song, and Yao (2017) apply the concept to the US mortgage market defining as add-on the mortgage contract features after the end of an initial fixed rate period. If these are too unattractive consumers can refinance with a competitor, but only sophisticated borrowers do so.

Specifically in our context, users of a mortgage split into several "tranches" with different maturities are typically barred from switching lenders when one tranche matures, because neither the bank with still running tranche nor any competitor willing to refinance the maturing one would accept to share their recourse to the collateral with another bank. Therefore the refinancing typically necessary after between 5 and 10 years would seem to fall in the category of an add-on,[17] while the purchase of other banking services such as an equity fund would count as cross-selling in a wider sense.

This means that onboarding of a new client typically implies not only the profits from the current financing but very likely also those from refinancing it later. In that setup, Klemperer (1995) predicts that investments into future market shares and hence lower markups now are more (less) attractive the greater (smaller) the expected future profitability of that market. On these grounds we posit:

Hypothesis 1: Given switching costs and future business, especially refinancing, banks are ***more*** *likely to offer, and offer* ***lower*** *prices, the more concentrated the local mortgage market has been so far.*

4.2. Strategy on local market concentration

Our key measure of the concentration of cantonal mortgage markets is the Herfindahl-Hirschmann Index (HHI), i.e., the sum of squared market shares in cantonal mortgage volumes.[18] We start with simple non-causal probit and logit regressions for the binary outcome offer, and with OLS regressions of the continuous outcome price. In Table 2 and various subsequent tables, we always have it that columns 1 and 2 control for both household and bank characteristics, columns 3 and 4 replace bank controls with bank fixed effects,[19] and columns 5 and 6 also replace household controls with household group fixed effects. These groups are based on almost the full set of household characteristics, including their LTV bracket, their LTI bracket and an indicator for refinancing rather than new borrowing, as well as year and month fixed effects. The only characteristic not included in the group definition is location to avoid collinearity with HHI.

One issue this creates is that different banks' prior presence as well as current online offer behavior may be influenced by the same unobservable. In particular, non-causal estimates are likely to be biased toward zero: Unobservable factors that increase the attractiveness of lending to a certain canton are likely to have motivated more banks to start lending there in an offline world, thus reducing market concentration, and to incentivize more and more attractive offers also online. This could bias us to find more attractive offers going to less concentrated markets, biasing downward our estimates of interest.

To address this concern, we exploit the fact that precisely during the years of interest mortgage market concentrations fell in most Swiss cantons, after the then Big Two banks UBS and Credit Suisse (CS) had experienced drastic losses in the US market and suffered hefty subsequent deposit withdrawals by their Swiss customers. As a consequence, their Switzerland-wide mortgage portfolios ended up growing only about half as fast as that of the market as a whole. This opened up opportunities for other banks and more so in cantons with higher initial market shares held by the Big Two.[20] Overall other banks jumped in enough that total supply kept growing as fast as before or after, cf. ***Appendix*** *Fig. 1*.

More specifically, our baseline analyses instrument the HHI in each canton and year with the product of a national *shift*, the national shortfall of Big 2 relative to market-wide mortgage growth,[21] and the *shares* of the Big Two in each canton in 2009, before the shift.[22] Prior cantonal market shares of the Big Two ranged between 9 % and 57 %, so our strategy compares the effect of the same shift in cantons with more than half of the market held by the Big Two to cantons with less than 10 % held by them, and conceptually constructs the counterfactual of a canton with a zero market share and hence no impact of the Big Two mortgage lending reduction.

Looking at the changes in cantonal market shares based on banks' full balance sheets confirms that in the course of our sample they fell in 25 of 26 cantons, confirming that the developments were not specific to online behavior. More importantly, these changes exhibit a correlation of only 0.07 with prior market concentration, refuting the concern that the Big Two withdrawal was chosen in response to expected profitability in different cantons.

Further, we note that robustness checks available on request yield essentially the same results as in our baseline when first we use as *endogenous regressor* year-on-year changes rather than levels of HHI, when second, we use as *shift* the federal changes in HHI rather than the federal deviation of Big Two lending from market lending, or when third

[16] In line with this Click or tap here to enter text.Basten and Mariathasan (2023)Click or tap here to enter text.find that Swiss banks decided to leave deposit rates non-negative despite negative interbank rates. This made deposits loss-making, but allowed retaining clients for future business.

[17] In the market studied many mortgages consist of 2-3 «tranches» of different maturity (0-10 years). When one matures it must be refinanced. But other tranches that have not matured yet cannot be repaid early without high prepayment fine and lenders do not lend against collateral pledged also to another lender. So the lender can dictate the price, see https://www.hypoplus.ch/de/hypotheken-ratgeber/gestaffelte-hypotheken-vorsicht-mit-tranchen.html or https://moneypark.ch/news-wissen/hypotheken-und-zinsen/hyposplitting-macht-kaum-je-sinn/

[18] Not only do we not have all data for regions more granular than the 26 cantons, but cantons are also considered separate but entire markets by many Swiss practitioners. This is so because at least traditionally many cantonal banks had mandates restricting which cantons (often their home plus directly neighboring ones) they could lend to, although more recently these restrictions were often loosened. In addition, many regional banks, much smaller than cantonal banks, had no formal restriction but preferred to stay in their home canton before hedonic models started facilitating property valuation also elsewhere.

[19] Adding bank controls renders, if anything, estimates that are larger in absolute value and statistically more significant throughout. We choose to display the more parsimonious and conservative estimates.

[20] Year-on-year mortgage growth of the Big Two returned roughly to the market average by the end of our sample, but our instrument exploits only that part of the variation in cantonal HHI induced by below-average growth.

[21] Our baseline computes market growth including the Big Two. In a variation which excludes the Big Two from the market, differences are even larger but our estimates are similar. They are available on request.

[22] Shares from earlier years can also be used but differ little as on-balance volumes are slow-moving.

Table 2
Non-causal analysis of bank responses and market concentration levels.

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer 2SRI	(6) Price
HHI	0.48*	−0.39***	0.83***	−0.46***	1.22***	−0.46***
	(0.28)	(0.05)	(0.29)	(0.05)	(0.43)	(0.03)
I(LTV>=67 %)	−0.05	0.05***	−0.05	0.05***		
	(0.03)	(0.01)	(0.03)	(0.01)		
I(LTV>=80 %)	−0.84***	0.00	−0.86***	0.00		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(LTI>=4.5)	−0.19***	0.01	−0.18***	0.01		
	(0.03)	(0.01)	(0.03)	(0.01)		
I(LTI>=5.5)	−0.84***	0.02	−0.84***	0.02*		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.10***	0.03**	0.10***	0.03**		
	(0.03)	(0.01)	(0.03)	(0.01)		
House price growth	0.64	−1.16***	0.89*	−1.15***		
	(0.45)	(0.16)	(0.47)	(0.15)		
Number of Web Providers	0.02***	−0.01***	0.02***	−0.01***		
	(0.01)	(0.00)	(0.01)	(0.00)		
Ln(Total Assets)	0.06***	−0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.01***	−0.00***				
	(0.00)	(0.00)				
Deposits/TA	−0.02***	0.00				
	(0.00)	(0.00)				
Equity/TA	0.02**	0.02***				
	(0.01)	(0.00)				
Constant	−0.18	1.37***	0.75***	1.12***		1.01***
	(0.23)	(0.05)	(0.23)	(0.02)		(0.02)
d(Offer)/d(HHI)	0.11*		0.19***		0.29***	
	(0.07)		(0.07)		(0.10)	
Observations	25,125	20,583	25,113	20,583	24,428	20,583
Estimation	Probit	OLS	Probit	OLS	Logit	OLS
Bank FE	No	No	Yes	Yes	Yes	Yes
HH Group FE	No	No	No	No	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	No	No
Effect of 1SD of HHI	0.22	−0.02	0.04	−0.02	0.06	−0.02

HHI is the Herfindahl-Hirschmann Index (HHI), i.e., the sum of squared market shares, in cantonal mortgage markets in the year of the bank response. Household controls include indicators for loan-to-value (LTV) ratios above 2/3 and above 80 %, for Loan-to-Income (LTI) ratios above 4.5 and above 5.5, and for a new rather than refinancing mortgage application, as well as cantonal house price growth and the number of other banks also offering online to that canton. Bank controls include the log of the responding bank's total assets and the shares in total assets of respectively mortgages, deposits, and equity. Columns with unequal numbers analyze banks' response to HHI in terms of offer propensities using (IV) Probit regressions (except for Column 5 due to the incidental parameter problem, see text), Columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1–2 use both household and bank controls, 3–4 replace bank controls with bank fixed effects, while 5–6 also replace household controls with fixed effects for household groups constructed from the LTV range, the LTI range, the refinancing indicator, a year dummy and a month dummy. See text for the rationale. At the bottom, we rescale these effects more realistically by the standard deviation (SD) of HHI. i.e. 0.05. Standard errors in parentheses are clustered by household group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

we use Big Two deposit rather than mortgage market *shares* in each canton.

The strategy to exploit pre-existing variation in market shares to obtain differential exposure to a supply-side shock is similar to strategies recently used by Mian and Sufi (2012), Chodorow-Reich (2014), D'Acunto and Rossi (2021), and Gete and Reher (2018). Chodorow-Reich also discusses how Credit Suisse was hit hard by losses in the US mortgage-backed securities market and so had to reduce amongst others its US syndicated lending. In contrast to those papers which focus on effects of losses or higher costs in the US on some segment of US lending, we exploit the fact that following their losses in the US the Swiss Big Two had to also cut their lending at home, which reduced market concentration in particular in those cantons where the two had the largest market shares before.

The episode and its exogeneity to Swiss mortgage markets is discussed in more detail also in Brown et al. (2020) and partially in Blickle (2022). The former paper analyzes how households were quick to withdraw deposits from the Big Two, stressing the importance of bank household relationships. Blickle (2022) additionally exploits that where the Raiffeisen network of cooperative banks had branches close to UBS branches, significant portions of the deposit outflows from UBS went to Raiffeisen banks and enabled them to increase mortgage lending. Here we go one step back and focus on the fact that, while selected Raiffeisen banks could *increase* their mortgage lending following the deposit inflows, UBS and CS had to *decrease* theirs following their deposit outflows. While the opportunities of the Big Two to borrow without collateral from banks without overseas losses or deposit withdrawals were limited, the Swiss National Bank (SNB) orchestrated an opportunity for them to issue additional covered bonds and so borrow against collateral through the so-called "Limmat transactions" in 2008 and 2009.[23] This reduced their liquidity shortages and the size of the necessary recapitalizations in 2008, in the case of UBS provided through a government bail-out.[24] Yet given capital constraints new lending was not a priority, especially for mortgages where the relationship component was arguably less important than for corporate lending.

As pointed out recently in the economics literature by Borusyak et al. (2021) and Goldsmith-Pinkham et al. (2020), the validity of a Bartik or shift-share instrument requires that *either* shifts or shares, or both, are uncorrelated with the outcomes of interest through channels other than the instrumented variable. In our setup this seems a priori most convincing for the shifts as the timing of the different shortfalls of

[23] For more details, see https://www.fuw.ch/article/der-stille-retter-der-grossbanken/, accessed October 23, 2019.

[24] See e.g. https://www.theguardian.com/business/2008/oct/16/ubs-creditsuisse accessed on October 23, 2019.

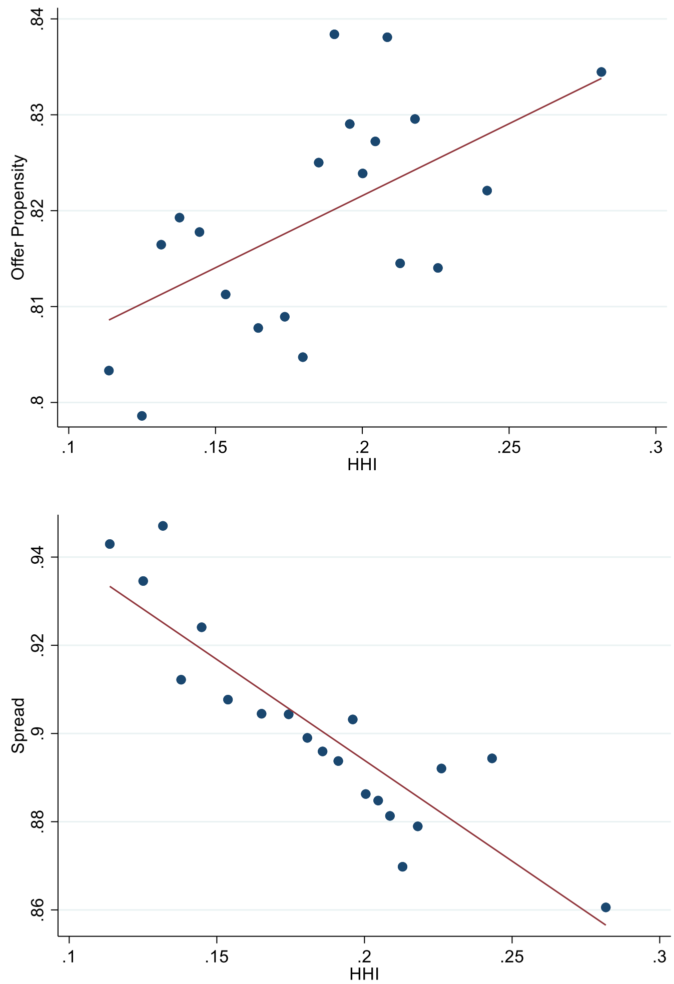

Fig. 1. Bin scatter plots for offer propensity and pricing against HHI
The upper panel plots average offer propensities against average values of HHI for 20 equally sized (by the number of bank responses) bins of HHI values. The lower panel does the same for the outcome weighted spread. Both panels residualize the averages for both household group and bank fixed effects, but do not instrument. Results are similar, but slightly noisier without any controls, and more precise if we also absorb residuals from first-stage regressions, all of which are available on request.

national Big Two mortgage growth relative to market-wide mortgage growth was driven by the lags with which the extent of their overseas losses became known and were responded to. And the Big Two, whose overseas losses trigger the shifts in local cantonal market concentration, are not part of our sample. Instead, our sample focuses on the behavior of local banks with no noteworthy exposure to US subprime markets in earlier years. So, we do *not* need to assume exogeneity of the shares, which we would *not* deem sufficiently plausible.

At the same time, Borusyak et al. (2021) point out that for a shift-share estimator to be consistent one needs “many” shifts, whereas our setup provides us with merely five different shift years. It is therefore comforting to see that when we compute standard errors as recommended for shift-share estimators by Adão et al. (2019), our standard errors do not become larger, suggesting that the correlation of residuals in cantons with similar shares is likely not an issue in our setup.

Yet we move on to consider explicitly if correlates of prior market shares could potentially bias our results. Looking at overall fairly persistent Big Two market shares reveals those to be larger in more urbanized cantons which historically industrialized earlier, because the predecessors of the Big Two started out as corporate lenders. Therefore, ***Appendix*** *Table 1* controls explicitly for cantonal population density and the population shares who are respectively foreigners, aged above 64, or live in urban areas. It also controls for unemployment rates, GDP per capita, the share of employment in the secondary and third sector respectively, and the population share with a tertiary education. Finding none of these to significantly change our results suggests that results are unlikely to be driven by correlates of prior, cross-sectional market shares.

For the continuous outcome pricing we can implement the instrumental variable (IV) procedure as simple two-stage least squares (2SLS) regressions, regressing in the first stage the HHI on the instrument and in the second stage pricing on the HHI prediction from our first-stage estimates. For the binary outcome offer we can also do this, but we prefer a non-linear estimator to better account for the binary nature of the outcome. Further, to avoid the large number of fixed effects causing an incidental parameter problem with too few observations per cross-sectional unit (Greene (2004)), we use logit rather than probit estimators. Following Abrevaya (1997), this can then be implemented as conditional Maximum Likelihood Estimator and thereby circumvent the incidental parameter problem.

Finally, the move from probit to logit in turn means that implementing the IV method through predictor substitution, i.e., by replacing in stage 2 the endogenous regressor with its predictor obtained in the first stage, is inconsistent. Following Terza et al. (2008) however, a consistent estimator can still be obtained by implementing the IV estimation through two-stage residual inclusion (2SRI). Here stage 2 includes the endogenous regressor itself, rather than its predictor, but it controls in stage 2 for the residuals from stage 1. Letting subscript i denote individual households nested in household groups g, letting b denote banks, and $\widetilde{HHI}_i$ the prediction for HHI_i based on our 1st stage, our 2SLS equation is

$$Y_{i,b} = \alpha + \beta(\widetilde{HHI}_i) + \delta_g + \mu_b + \varepsilon_{h,b} \tag{1}$$

By contrast, our 2SRI equation includes HHI_i itself, but controls for the 1st stage residual $R_{i,b}$:

$$Y_{i,b} = \alpha + \beta(HHI_i) + \delta_g + \mu_b + \tau\left(R_{i,b}\right) + \varepsilon_{h,b} \tag{2}$$

While our later analyses on risk management and automation can include both bank and household fixed effects, here we use household *group* fixed effects, where groups are based on *all* household characteristics except for their location. This is because our main regressor of interest, HHI, varies by canton and hence does not vary within each household.

Following Bertrand et al. (2004), at the baseline we cluster our standard errors by the panel dimension, i.e., by the 708 household groups for our market concentration analyses and by the 6914 households for our risk management analyses. Robustness checks available on request, which cluster instead by the 7442 bank * household zip code pairs, or by the 173 bank * household canton combinations, yield qualitatively the same results. All of these options have more than 50 clusters as recommended by Cameron and Miller (2015) and none of them contains more than 5 % of observations, as recommended by Rogers (1993), both guidelines of which would be violated if we clustered by the 26 banks or 26 cantons only.

For our shift-share estimates we compute also standard errors following the procedures recommended for shift-share designs by Adão et al. (2019). As their procedure is so far available for linear estimators only, we use the linear probability model rather than probit or logit also for the binary outcome offer. We find that in our setup standard errors computed in this way are not significantly larger than standard cluster-robust standard errors. Therefore, our baseline estimates use the latter so that we can use also non-linear estimators for the outcome offer.

4.3. Results on local market concentration

Table 2 starts with non-causal regressions of respectively offer dummy (columns 1, 3 and 5) and pricing (columns 2, 4 and 6) on the HHI level. Gradually increasing the conservativeness of our model, columns 1 and 2 use bank and household controls, 3 and 4 use bank fixed effects and household controls, and 5 and 6 use both bank and household group fixed effects as discussed above.[25] While columns 1 and 3 have only few fixed effects and can hence use probit estimation, column 5 uses logit estimation to mitigate the incidental parameter problem. While line 1 displays the coefficients, the line below the constant shows the implied average marginal effects (AME) which coincide with the coefficients for the OLS estimation for pricing, but differ for probit and logit estimations. We find across all three specifications that higher HHI levels are associated with higher offer propensities as well as a price discount, all statistically significant at the 1 % level except for column 1 which is significant at the 10 % level only.

To convey the same relationships also visually, *Fig. 1* groups the range of observed HHI values into 20 bins containing an equal number of bank responses each. It then plots for each of these bins the corresponding average offer propensity in the upper panel and the average spread offered in the lower panel respectively. To make the figure correspond to our estimations, both HHI and the two outcomes are residualized for the same sets of controls as used in our regressions. So, the figure reveals also visually that more market concentration induces banks ceteris paribus to offer more often and at lower prices.

Table 3 then presents our main IV estimations. To start with the first stages, Columns 1, 4 and 7 show that, across all specifications, a Big Two year-on-year mortgage growth of one percentage point above (below) that of the market is, for a hypothetical canton with a Big Two market share of unity (hundred percent), predicted to increase (decrease) the cantonal HHI by 0.04 index units. With an average shift of −2.1, i.e., with national Big Two mortgage growth being on average 2.1 pp below the market wide growth, we get an average HHI change of −0.03 index points. In our preferred specification, banks raise offer propensities by 0.82 and lower prices by −2.35 times that HHI change. Hence, we can summarize the economic magnitude of the effects of interest by saying that the offer propensity is 0.03 pp higher and the pricing 6 bps lower in response to the on average 0.03 unit reduction in cantonal HHI.

Both the estimated effects on offer propensities and those on pricing go in the same direction but are between 2.5 and 5 times as large as the corresponding OLS estimates. This is in line with our reasoning above, whereby the same unobservables at the canton level are likely to have affected banks' eagerness to lend there offline and hence prior market concentration as well as affecting banks' current eagerness to lend to a canton online, thus causing non-causal estimates to be biased toward zero.

We rationalize the greater eagerness to enter more concentrated markets with more profitable follow-on business. While we do unfortunately not directly observe follow-on business, this reasoning is strongly supported by practitioner statements such as a recent interview by the CEO of Glarner Kantonalbank, one of the pioneers of Swiss online mortgages, who said: "Through the online channel we gain many new customers … Then we seize the cross-selling potential for follow-on business … the Risikomat [an online whole life insurance product] is primarily a cross selling product sold with online mortgages".[26]

Here we also briefly discuss banks' responses to households' and banks' own characteristics, which can help to better understand the setup. For household characteristics we focus on indicators for LTV ratios above 67 % and 80 % and loan-to-income (LTI) ratios above 4.5 and 5.5 respectively. The specific LTI thresholds reflect frequent practice in the market,[27] while LTV thresholds correspond to those above which Swiss banks following the Basel Standardized Approach (all banks in our sample) face higher risk weights leading to higher capital requirements and therefore higher refinancing costs, see Basten (2020). The threshold indicators turn out to have stronger effects on the outcomes of interest than continuous LTV or LTI variables. In robustness checks available on request, continuous LTV and LTI ratios fail to have a statistically significant effect on our outcomes of interest after controlling for the indicators displayed here. Further, in line with common practice at the banks studied, we focus on the two risk characteristics LTV and LTI. When we additionally control for a household's total income, rental income, or non-labor income, for household wealth including or excluding pension fund wealth, debt, age or the type of dwelling sought, which are also observed in addition to LTV and LTI, none of them changes significantly the coefficients of interest.

As one would expect, we find throughout that higher LTV or LTI ratios induce banks to offer less often and, conditional on still offering, to add a risk premium and therefore charge higher prices. This is in line with, amongst others, Campbell and Cocco (2015), who point out how higher LTV ratios tend to be associated with higher credit risk in mortgage lending. The roughly 50 % of applications asking for banks to finance a new real estate purchase rather than to refinance an older mortgage, tend to receive more offers, in line with the fact that such clients can be expected to yield business for longer. At the same time, they are offered higher rates, even after controlling for the now on average lower LTV and LTI ratios, which may reflect that first-time buyers have not yet been screened by another bank and have not yet proven their ability and willingness to keep servicing their mortgage.

Looking at bank characteristics, we see that banks which are either larger in terms of total assets or have a larger fraction of their assets dedicated to mortgage lending offer more often and at lower prices. One plausible explanation of this finding, beyond risk management, is higher operational efficiency. By contrast, banks that raise a larger fraction of their funding through deposits offer less often. Here one possible reason is that having more depositors provides a bank already with a larger pool of potential mortgage clients, so that it may be less eager to also sell mortgages online. Further, in contrast to the second most important source of funding for Swiss commercial banks, covered bonds, deposits have shorter contractually guaranteed rate fixation periods. Thus, financing mortgages – the majority of which carries fixed rates – with deposits tends to yield a profitable margin in the short run, but implies also more interest rate risk to be borne or hedged at a cost. Further, better capitalized banks tend to charge higher prices, possibly reflecting that a larger fraction of funding raised through equity may be thought to

[25] Using both bank fixed effects and bank controls simultaneously yields very similar coefficients of interest as does the use of bank fixed only given limited intra-bank variation in bank controls.

[26] https://www.moneycab.com/interviews/hanspeter-rhyner-vorsitzender-der-geschaeftsleitung-der-glkb-im-interview/

[27] In particular, banks deem applicants riskier if their *Payment*-to-Income (PTI) ratio exceeds 1/3. For computing the PTI ratio during the period analyzed, banks used «stress-test» interest rates of either 4.5% or 5%. In addition, they assumed house maintenance costs amounting to either 1% of the loan value, or 1% of the house value, implying 1.5% of the loan value at an LTV ratio of 2/3. Finally, amortization was assumed to be either 1% of the loan value, or 0% when regulation did not require it due to an initial LTV ratio below two-thirds or before June 2012. Overall the 9 resulting combinations implied annual mortgage service payments ranging between 5.5% and 7.65% of the loan. The requirement for this to not exceed 1/3 was then equivalent to LTI thresholds of between 4.36 and 6.06. Here we round these to 4.5 and 5.5, as these are LTI cutoffs used in regulation, e.g., in the UK.

Table 3
Instrumental variable (IV) analysis of bank responses to market concentration.

	(1) HHI	(2) Offer	(3) Price	(4) HHI	(5) Offer	(6) Price	(7) HHI	(8) Offer	(9) Price
HHI		2.21	−2.18***		4.93***	−1.69***		17.00***	−2.35***
		(1.41)	(0.24)		(1.48)	(0.22)		(4.42)	(0.30)
Shift*Share	0.04***			0.04***			0.04***		
	(0.00)			(0.00)			(0.00)		
I(LTV>=67 %)	−0.00***	−0.05*	0.05***	−0.00***	−0.04	0.05***			
	(0.00)	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)			
I(LTV>=80 %)	0.00	−0.85***	0.03***	0.00	−0.85***	0.03***			
	(0.00)	(0.05)	(0.01)	(0.00)	(0.05)	(0.01)			
I(LTI>=4.5)	0.01***	−0.19***	0.01***	0.01***	−0.19***	0.01**			
	(0.00)	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)			
I(LTI>=5.5)	−0.00***	−0.85***	0.02**	−0.00***	−0.84***	0.02***			
	(0.00)	(0.05)	(0.01)	(0.00)	(0.05)	(0.01)			
I(New Mortg.=1)	0.00***	0.09***	0.03***	0.00***	0.09***	0.03***			
	(0.00)	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)			
House price growth	1.13***	−2.85*	1.78***	1.16***	−4.01***	0.90***	0.96***		
	(0.02)	(1.58)	(0.25)	(0.02)	(1.39)	(0.19)	(0.02)		
Number of Web Providers	−0.00***	0.03***	−0.01***	−0.00***	0.04***	−0.01***	−0.00***		
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)		
Ln(Total Assets)	0.01***	0.05***	−0.03***						
	(0.00)	(0.02)	(0.00)						
Mortgages/TA	0.00***	0.01***	−0.00***						
	(0.00)	(0.00)	(0.00)						
Deposits/TA	−0.00***	−0.02***	−0.00						
	(0.00)	(0.00)	(0.00)						
Equity/TA	0.00***	0.04***	0.02***						
	(0.00)	(0.01)	(0.00)						
Constant	0.13***	−0.53*	1.73***	0.22***	−0.03	1.40***	0.21***		1.38***
	(0.01)	(0.28)	(0.05)	(0.00)	(0.37)	(0.05)	(0.01)		(0.06)
d(Offer)/d(HHI)		0.52	−2.18***		1.15***	−1.69***		0.82*	−2.35***
		(0.33)	(0.24)		(0.35)	(0.22)		(0.47)	(0.30)
Observations	25,125	25,125	20,583	25,125	25,113	20,583	25,125	24,428	20,583
Estimation	OLS	IV Probit	IV	OLS	IV Probit	IV	OLS	2SRI Logit	IV
Bank FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
HH Group FE	No	No	No	No	No	No	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Effect of 1SD of HHI		0.03	−0.11		0.06	−0.08		0.04	−0.12

HHI is the Herfindahl-Hirschmann Index (HHI), i.e., the sum of squared market shares, in cantonal mortgage markets in the year of the bank response Columns 1, 4 and 7 show the first stages, regressing the HHI on the instrument, product of Shift and Share. The Shift is Switzerland-wide year-on-year mortgage growth of the Big 2, less that of the entire market. Shares are cantonal market shares of the Big 2 in 2009. Columns 2, 5 and 8 show IV estimates for the causal effect of HHI on Offers. As the outcome is binary, 2 and 5 use Probit in the 2nd stage of the 2-Stage Least Squares (2SLS). Column 8 uses Logit to avoid the Incidental Parameter problem. As Logit is not possible with 2SLS, we combine it with a 2-Stage Residual Inclusion (2SRI) of the IV estimation. Columns 3, 6 and 9 use as outcome the continuous variable Price. Columns 1–3 control for household and bank characteristics, 4–6 replace bank characteristics with bank fixed effects, 7–9 replace also household characteristics with household group fixed effects. Below the constant we display the average marginal effects of moving from perfect competition (HHI=0) to perfect monopoly (HHI=1). At the bottom, we rescale these effects more realistically by the standard deviation (SD) of HHI, i.e. 0.05. Standard errors in parentheses are clustered by household group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

imply (more safety in crisis times but also) higher costs per unit of lending.

4.4. Robustness of responses to market concentration

Exploring the robustness of Table 3 results, ***Appendix Table AT1*** controls for an extensive set of canton-level observables. This makes effects on offering slightly larger and those on pricing slightly smaller, but all retain their directions and statistical significance.

Next, ***AT2*** explores the use of AKM standard errors. As the procedure is not so far available for non-linear estimators, columns 1, 3 and 5 use the linear probability model (LPM). To start with, we find marginal effects on offer probabilities of 0.58 compared to 0.52, 1.17 compared to 1.15, and 1.18 compared to 0.82, so the LPM yields point estimates for the marginal effect which by and large confirm those obtained through non-linear procedures. Further, standard errors for the outcome pricing, where point estimates are identical, are slightly smaller rather than larger. This holds both when we use the "AKM1" procedure as displayed here, or the "AKM0" alternative also described by AKM. This reduces concerns about the limited number of shifts in our setup.

While the most common measure of market concentration is probably the HHI, another measure used, e.g., in Degryse and Ongena (2007) is the measure of Multi-Market Contact or Competition (MMC). It sums the number of bank pairs present after weighing each pair by the number of other cantons in which this pair also does encounter each other. More formally, we denote the 26 cantons by indicator *j,* and the 180 banks with any mortgages in 2009 by indicators *k* and *l.* Then we let $D_{ij} = 1$ if bank *i* operates in canton *j* and 0 otherwise. So $a_{kl} = \sum_{j=1}^{26} D_{kj} D_{lj}$ tells us for each pair of banks *(k,l)* in how many of the 26 cantons they encounter each other, and f_j indicates how many pairs of banks we encounter in canton *j*. Based on this, we compute $MMC_j = \frac{2}{26 f_j (f_j - 1)} \sum_{k=1}^{180} \sum_{l=k+1}^{180} a_{kl} D_{kj} D_{lj}$. The measure follows the idea in Edwards (1955) of a "linked oligopoly" under which multi-market contact increases banks' incentives to collude and hence leads them to behave less competitively. On the other hand, Park and Pennacchi (2009) find that the presence of more multi-market banks can *promote* more competitive behavior. So we need to analyze our data to find out which effect dominates.

In ***AT3***, Columns 1, 3 and 5 tell us that an increase in the MMC measure by 1 unit increases the offer propensity by 24–52 pp, while columns 2, 4 and 6 find the same increase to additionally lower prices by

25–86 bps, and except for column 5 all estimates are statistically significant at 1 % or lower. This is more in line with the findings of Park and Pennacchi (2009), whereby multi-market contact promotes competitive behavior, than with the original "linked oligopoly" hypothesis of Edwards (1955) whereby it promotes collusion. We note though that since MMC is computed using information on all columns, it does not lend itself to instrumentation with our shift-share instrument given the cantonal variation in shares and so our MMC estimates are descriptive and not necessarily causal.

Table 4 repeats the IV analyses from Table 3 but includes controls for both PD and LGD complementarity between borrower and lender canton. The direction and statistical significance of our coefficients on HHI remain broadly unchanged. So do coefficient sizes as long as we use household controls, whereas they roughly double in size when we use household group fixed effects. This confirms that bank responses to prior competition are not just driven by risk management considerations, which we analyze on their own with more appropriate specifications in the following section. Nor are they driven by soft information or adverse selection as we observe and control for all information lenders have, and show in the appendix that platform users are not found to be riskier than offline borrowers.

5. Responses to diversification opportunities

5.1. Hypothesis on diversification opportunities

Petersen and Rajan (2002), Degryse and Ongena (2005) and Agarwal and Hauswald (2010) analyze how credit availability and pricing are related to borrower-lender distance, but all focus on corporate lending. While Degryse and Ongena focus on banks' ability to charge a higher margin to nearby firms for sparing them commuting time, Agarwal and Hauswald add the role of distance for the collection of soft information and find closer firms to get more credit but at higher cost.[28] Petersen and Rajan find the role of distance for corporate lending to decrease due to advancements in technology. This selection of papers shows that *distance* per se is ambiguous as it may matter both for banks' ability to screen and monitor, and for their ability to extract margins based on borrowers' travel times and competition. For this reason, we focus our analysis of risk management incentives on two more specific proxies for respectively probabilities of default and loss given default, before horse racing those with distance.[29]

Going beyond simple borrower-lender distance and looking at the marginal contribution of each loan to the lender's portfolio risk, one possibility is for the lender to reduce risks to its portfolio by allocating more of its new lending to regions where default rates or collateral values are less correlated with those at home. In this vein, Quigley and van Order (1991) analyze how actual mortgage defaults in the US are correlated intra- and inter-regionally and infer that mortgage portfolios are indeed riskier if they are less regionally diversified.[30] On the other hand, a bank's risk managers may instead prefer to focus lending on fewer regions so that it pays to collect more information there. This argument is made by Loutskina and Strahan (2011) and empirically confirmed for the US market. Further, Favara and Giannetti (2017) show that a bank with many mortgages in the same region can better internalize the negative externalities of collateral liquidations on the prices of other nearby collateral in an episode of increased defaults, and likewise Favara and Giannetti (2017) and Giannetti and Saidi (2019) find an internalization of spill-overs from the liquidation of firm loans in more concentrated industries. This per se would speak in favor of seeking to sufficiently dominate one area to internalize and so ideally remove that externality.

To assess whether the benefits of hedging against idiosyncratic local risk or agency problems associated with greater distance dominate empirically, Goetz et al. (2016) analyze the effects of US interstate branching deregulation. They find that it does overall reduce bank risk, both when measured as the standard deviation of bank stock returns and when measured by other measures. This is so despite the fact that Goetz et al. (2013) find greater regional diversification to reduce banks' average stock prices. In fact, already Berger and DeYoung (2006) show that technological progress, associated in their case with more credit scoring based on more hard rather than soft information as well as with more advanced telecommunication technologies, can reduce the agency costs associated with greater distance. This confirmed empirically the theoretical arguments in Stein (2002).

In the segment of residential mortgage lending studied here, regulation effectively restricts the maximum loan-to-value (LTV) ratio to 90 % and the maximum loan-to-income (LTI) ratio to effectively 6, so that arguably none of the mortgages are as risky as some uncollateralized lending can be. More importantly, collateral values are typically not assessed physically, but through hedonic models bought from one of three consulting companies and are based on the *same* model for all of Switzerland.[31] Finally, all banks have the same hard information on each customer and no soft information. So the context complies very much with one characterized by Stein (2002) as based fully on hard rather than soft information.[32] The only dimension along which a geographically closer bank might reach a different assessment on the basis of the same information is that it may attach a different value to the applicant's postcode area than a bank with less local knowledge. So we expect diversification to dominate:

<u>Hypothesis 2:</u> *Banks are more likely to offer, or offer lower prices, when unemployment rates as proxies for default probabilities, or house value changes as proxies for loss given default, have historically exhibited a* ***lower correlation*** *between the applicant's and the bank's canton.*

5.2. Strategy on diversification opportunities

We focus on two measures relevant for banks' portfolio risk management. First, we use the correlation of unemployment rates between bank and borrower canton as a proxy for inter-regional complementarity of probabilities of default. Second, we use the correlation of house price changes between bank and borrower canton as a proxy for the inter-regional complementarity of loss given default.[33] They are based on growth rates in a house price index for medium-quality apartment prices since 1985 from FPRE consultants. Using instead price growth for low- or high-quality apartments, or for single-family homes, yields very similar regression results. The frequency is annual, but correlations

[28] In the same vein, Eichholtz et al. (2023) find US banks to increase margins in distance when pricing mortgages underlying CMBS and interpret their measure of distance as a proxy for less soft information.

[29] Other than in the US, prepayment risk is not relevant for Swiss mortgage lenders, as prohibitive prepayment penalties rule out strategic prepayment.

[30] More recently Click or tap here to enter text.Deng, Mao, and Xia (2021) find bank diversification to benefit corporate innovation and Click or tap here to enter text.Levine, Lin, and Xie (2021)Click or tap here to enter text. find it to benefit bank funding costs.

[31] See e.g. https://www.iazicifi.ch/produkt/immobilien-online-bewertung/ , one of the three main model providers who write that "The hedonic method is standard for mortgage lending in Switzerland. Various big banks, cantonal banks, and regional banks … use the IAZI model." Accessed in April 2021.

[32] E.g. Swiss business newspaper Handelszeitung writes in 2013, before Comparis bought human broker firm Hypoplus: "Another platform, which … [provides customer-specific pricing], is the price comparison website Comparis. ch … The six to seven offers arrive electronically within 2 days. *As applicants remain anonymous vis-à-vis lenders* …, lenders must offer aggressively", https://www.handelszeitung.ch/geld/online-hypotheken-shopping-vergleichen-und-sparen , accessed 4/2021.

[33] For context, the median bank in our sample has 89% of its existing mortgage portfolio in its home canton, the mean bank 76%. Figures are even higher for the share in home or directly neighboring canton.

Table 4
Responses to market concentration combined with risk management.

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
HHI	1.68	−2.38***	5.90***	−1.95***	35.50***	−5.04***
	(1.62)	(0.29)	(1.96)	(0.33)	(9.65)	(1.02)
U Comp	1.41***	−0.27***	0.34	−0.10**	1.89***	−0.17***
	(0.31)	(0.06)	(0.35)	(0.05)	(0.57)	(0.06)
HP Comp	−0.10	0.08***	−0.36**	0.07**	−4.20***	0.50***
	(0.11)	(0.02)	(0.16)	(0.03)	(1.09)	(0.11)
I(LTV>=67 %)	−0.05*	0.04***	−0.04	0.05***		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTV>=80 %)	−0.85***	0.03***	−0.85***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(LTI>=4.5)	−0.19***	0.01***	−0.20***	0.01**		
	(0.03)	(0.01)	(0.03)	(0.00)		
I(LTI>=5.5)	−0.85***	0.02**	−0.83***	0.02***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.10***	0.03***	0.09***	0.03***		
	(0.03)	(0.00)	(0.03)	(0.00)		
House price growth	−2.49	2.00***	−4.74***	1.11***		
	(1.80)	(0.30)	(1.68)	(0.26)		
Number of Web Providers	0.02***	−0.01***	0.04***	−0.01***		
	(0.01)	(0.00)	(0.01)	(0.00)		
Ln(Total Assets)	0.04**	−0.03***				
	(0.02)	(0.00)				
Mortgages/TA	0.02***	−0.00***				
	(0.00)	(0.00)				
Deposits/TA	−0.01***	−0.00				
	(0.00)	(0.00)				
Equity/TA	0.06***	0.02***				
	(0.02)	(0.00)				
Constant	0.55	1.58***	−0.18	1.41***		2.24***
	(0.38)	(0.06)	(0.71)	(0.11)		(0.33)
Observations	25,060	20,533	25,048	20,533	24,326	20,533
Estimation	IV Probit	IV	IV Probit	IV	2SRI Logit	IV
Bank FE	No	No	Yes	Yes	Yes	Yes
HH Group FE	No	No	No	No	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	No	No

The IV strategy for HHI and all other choices follow those underlying Table 3. But in addition we control here for the unemployment rate complementarity (U Comp), i.e., the inverse of the unemployment rate correlation between borrower and lender canton. We also control for the house price change complementarity (HP Comp), i.e., the inverse of the correlation between the year-on-year percentage change in house prices in borrower and lender canton. Beyond these two additional controls, the notes of Table 3 apply. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

would unlikely be much different at higher frequency as both labor and real estate cycles last many years.

Inter-cantonal correlations of all proxies are positive: Within a country as small as Switzerland subject to the same monetary policy it is hard to find a region whose house prices can be expected to *increase* when those elsewhere *decrease*. Yet despite a common monetary policy, summary statistics show that as different cantons specialize in different sectors and receive immigrants from different countries, some inter-cantonal correlations are as low as 0.15. We can summarize our analyses on complementarity thus:

$$Y_{h,b} = \alpha + \beta\left(Complement_{h,b}\right) + \delta X_h + \mu X_b + \varepsilon_{h,b} \tag{3}$$

Now the primary regressor of interest is portfolio complementarity instead of HHI. As that varies both within households and within banks, we can now use fixed effects for each household h rather than just for each household group hg, in addition to fixed effects for each bank b.

5.3. Results on diversification opportunities

As per our *Hypothesis 2*, Table 5 analyzes how banks' responses relate to the complementarity of unemployment rates in the applicant's canton with that in the bank's home canton, which typically makes up the majority of mortgages already on the bank's balance sheet. The complementarity is simply the inverse of the correlation, scaled between −1 and 1. Higher complementarity values imply lower correlations. So, unemployment as the key systemic driver of defaults in the applicant's canton increases less when those in the bank's home canton increase.[34] Again columns 1, 3 and 5 for the binary outcome offer display first the probit (logit) coefficients for all regressors, and below the constant we then display the associated average (across all observed values of complementarity) marginal effects. These estimated marginal effects tell us also the economic magnitude of banks' response to diversification opportunities: Offer propensities are implied to be up to 2.24 % higher and prices up to 2.3 bps lower when the unemployment rate correlation is 1SD or 0.07 units lower.

Interestingly, when we exclude same-canton pairs, close to one-quarter of responses, we find offer responses to be about 20 % stronger and pricing responses about 35 % weaker, but both remain significant. So, responses to portfolio complementarity capture both the dimension of own vs. other cantons and that of differences between different other cantons.

Relatedly, Table 6 replaces the complementarity measure based on unemployment rates with a measure based on house price changes, following the consideration that larger house price decreases in crises can imply higher loss given default (LGD). Here we find that a change in complementarity by 1SD or 0.19 units increases the offer propensity by up to 1.14 % and lowers the price by up to 1.14 bps. These responses are somewhat smaller than those to unemployment rate complementarity.

[34] Another important determinant of default, following conversation with practitioners, is divorce, but divorces are so far not known to exhibit any systemic cyclical patterns in Switzerland.

Table 5
Risk management through unemployment complementarity.

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
Unemployment Complementarity	1.36***	−0.33***	0.64***	−0.24***	2.41***	−0.25***
	(0.21)	(0.03)	(0.24)	(0.03)	(0.66)	(0.03)
HHI	0.17	−0.39***	0.49*	−0.43***		
	(0.26)	(0.03)	(0.27)	(0.03)		
I(LTV>=67 %)	−0.05*	0.05***	−0.05*	0.05***		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTV>=80 %)	−0.84***	0.02***	−0.85***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(LTI>=4.5)	−0.18***	−0.00	−0.17***	0.00		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTI>=5.5)	−0.86***	0.03***	−0.86***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.09***	0.02***	0.09***	0.02***		
	(0.03)	(0.00)	(0.03)	(0.00)		
Ln(Total Assets)	0.03**	−0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.02***	−0.00***				
	(0.00)	(0.00)				
Deposits/TA	−0.01***	0.00*				
	(0.00)	(0.00)				
Equity/TA	0.07***	0.01***				
	(0.01)	(0.00)				
Constant	0.90***	1.31***	1.67***	0.85***		0.72***
	(0.29)	(0.05)	(0.35)	(0.04)		(0.04)
d(y)/d(Complementarity)	0.32***	−0.33***	0.15***	−0.24***	0.10*	−0.25***
	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)
Observations	25,060	20,533	25,048	20,533	9689	20,533
Estimation	Probit	OLS	Probit	OLS	Logit	OLS
Bank FE	No	No	Yes	Yes	Yes	Yes
HH FE	No	No	No	No	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	No	No

The unemployment rate complementarity is the inverse of the correlation (scaled between −1 and 1) between unemployment rates in 1973–2019 (longest available period) in the canton of the applicant and those in the canton of the bank. HHI is the Herfindahl-Hirschmann Index for cantonal market concentration, all other controls as in main paper Table 2. Columns with unequal numbers analyze banks' response in terms of offer propensities using Probit regressions (except for Column 5 due to the incidental parameter problem, see text), Columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1–2 use both household and bank controls, 3–4 replace bank controls with bank fixed effects, while 5–6 also replace household controls with now full-fledged household fixed effects. Standard errors in parentheses are clustered by household. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This makes sense insofar as ideally the bank wants to keep the PDs in its entire portfolio low. Use of remaining collateral values in a foreclosure procedure becomes necessary only conditional on default and in addition will at least imply additional costs even when collateral values still exceed the remaining debt. Hence PD complementarity seems yet more important than LGD complementarity.

Focusing on the price response to more unemployment complementarity, a discount of 2 bps may seem small at first sight, but this is after fully controlling for all observable and unobservable bank and household characteristics. Since online offers from different banks should really differ only across the pricing dimension, a household who paid about CHF 100 to obtain different offers seems likely to pick the cheapest offer only. Thus Basten (2020) has shown with data from the same platform that banks who increased mortgage prices relatively more after an increase in capital requirements did then experience relatively slower mortgage growth, confirming that households do respond to price changes.

Fig. 2 conveys these results visually. The two upper panels show bank responses to unemployment complementarity of applicant and bank canton as used in Table 5, while the two lower panels show responses to house price change complementarity as used in Table 6. In both cases, the left panel shows offer responses while the right one shows pricing responses. As in *Fig. 1*, variables on the horizontal axis are grouped into 20 equally sized bins to facilitate visibility, and in all four panels a linear line is fit using all about 25,000 underlying observations. The figure thus shows also visually how banks offer more often and at lower margins when a loan to the applicant's canton is more complementary to its own canton in terms of unemployment rates or house price changes respectively.

When observing that banks are more willing to offer, and offer better prices to regions whose unemployment rates or house price growth are less correlated with those in the bank's home canton, we have interpreted this as banks seizing the opportunity of lending without branches to improve their risk management. Of course, we do not directly observe banks' reasoning behind their decisions and acknowledge that the arguable improvement in geographical diversification may also have come about without a conscious striving for it. But since either measure of complementarity is at least 18 % correlated with branch distance, the above findings could alternatively be explained by banks charging higher (lower) prices to customers for having to drive shorter (longer) distances to the nearest branch. At least that would be in line with the finding in Degryse and Ongena (2005), who find Belgian banks to charge lower borrowing rates to more distant firms. To investigate this further, ***AT4*** relates offer propensity and pricing to the distance between the applying household and the responding bank, both known to the level of about 4400 Swiss zip codes, while at the same time controlling for unemployment complementarity between the household's and the bank's canton. Again, columns 1–2 include bank and household controls, columns 3–4 replace bank controls with bank fixed effects, and columns 5–6 additionally replace household controls with household group fixed effects. Since both branch distance and unemployment complementarity vary both within each bank and within each household, we can additionally include columns 7–8, which instead of a separate fixed effect for each of the 708 household groups can include even a separate fixed effect for each of the 6914 households.

To start with, we find across all columns that banks make more and lower-margin offers to households from cantons with more

Table 6
Risk management through house price change complementarity.

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
House price change complementarity	0.24***	−0.03***	0.05	−0.05***	−0.05	−0.06***
	(0.07)	(0.01)	(0.09)	(0.01)	(0.26)	(0.01)
HHI	0.20	−0.40***	0.59**	−0.42***		
	(0.25)	(0.03)	(0.27)	(0.03)		
I(LTV>=67 %)	−0.05*	0.05***	−0.05*	0.05***		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTV>=80 %)	−0.84***	0.02***	−0.85***	0.03***		
	(0.04)	(0.01)	(0.04)	(0.01)		
I(LTI>=4.5)	−0.17***	−0.00	−0.17***	0.00		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTI>=5.5)	−0.86***	0.03***	−0.87***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.09***	0.02***	0.09***	0.02***		
	(0.03)	(0.00)	(0.03)	(0.00)		
Ln(Total Assets)	0.03**	−0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.01***	−0.00***				
	(0.00)	(0.00)				
Deposits/TA	−0.01***	0.00***				
	(0.00)	(0.00)				
Equity/TA	0.05***	0.01***				
	(0.01)	(0.00)				
Constant	0.02	1.54***	1.05***	1.04***		0.90***
	(0.24)	(0.03)	(0.26)	(0.03)		(0.02)
d(y)/d(Compl)	0.06***	−0.03***	0.01	−0.05***	−0.01	−0.06***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.05)	(0.01)
Observations	25,125	20,583	25,113	20,583	9759	20,583
Estimation	Probit	OLS	Probit	OLS	Logit	OLS
Bank FE	No	No	Yes	Yes	Yes	Yes
HH FE	No	No	No	No	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	No	No

The house price (HP) change complementarity is the inverse of the correlation (scaled between −1 and 1) between year-on-year house price changes in the canton of the applicant and those in the canton of the bank. HHI is the Herfindahl-Hirschmann Index for cantonal market concentration, all other controls as in main paper Table 2. Columns with unequal numbers analyze banks' response in terms of offer propensities using Probit regressions (except for Column 5 due to the incidental parameter problem, see text), Columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1–2 use both household and bank controls, 3–4 replace bank controls with bank fixed effects, while 5–6 also replace household controls with now household fixed effects. Standard errors in parentheses are clustered by household. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Columns with unequal numbers show marginal effects from Probit regressions. The correlation between past house price changes in the applicant's and the bank's canton is instrumented with an indicator for language mismatch between the two regions. The additional control relative over-heating indicates the estimated house price over-heating (i.e. actual over fundamentally justified house prices, as computed by FPRE consultants) in the applicant's relative to the bank's home canton. HHI in Columns 5 and 6 is instrumented by big banks' market share in 2009, as in Table 2. LTV is the loan-to-value, LTI the loan-to-income ratio of the applicant. About half of all applications are for refinancing a mortgage rather than for initial purchase. All estimations include year*month fixed effects to control for time trends. Standard errors clustered by bank * household zip in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

complementary unemployment rates. This supports the interpretation that banks can seize the online channel to support the geographical diversification of their portfolio, rather than just exploit the fact that they can charge higher prices to customers who would not have to commute as far for borrowing from that bank. The same holds also in robustness checks available on request which control for distance to the bank headquarter rather than to the nearest branch, as the majority of banks in our sample have their network of branches focused in or directly around the canton in which they are headquartered. Further, while the estimates presented here use geodesic distances, accounting for earth curvature but not for exact roads, we note that results are very similar when we use GIS based exact driving distances or times known only for a subset of household bank branch pairs.

At the same time, we also find that even after controlling for unemployment complementarity as well as for fixed effects both for each bank and for each household, branch distance itself also continues to exert a statistically significant effect, as in Agarwal and Hauswald (2010) decreasing credit availability but also decreasing prices. However, the economic significance of the marginal effects on pricing seems rather limited with 5–6 bps per 100 km and hence about 1 bp for the average distance of about 20 km. We rationalize a limited effect of distance per se, after controlling for more specific proxies for PDs and LGDs, as follows: while management of a corporate borrower may need to visit a bank branch repeatedly for example to increase, decrease or renew its loan, an online mortgage borrower typically needs to do so at most once and may hence not need to be enticed to drive with a price discount.

6. Automation

6.1. Hypothesis on automation

Any of the determinants of mortgage pricing discussed above can work through rules automated through a computer or common policies for staff to follow. Alternatively, if staff retains sufficient leeway, they may take into account also other factors. In the context studied, we have access to all hard information the bank received through the platform and would hence expect less heterogeneity in offers than in contexts in which loan officers may employ additional soft information. Yet we do expect more scrutiny for riskier applications as well as by banks who have less experience in the mortgage market as they are smaller or less focused on the mortgage business. Further, we expect that banks can increasingly automate their business the more experience they have already accumulated online. So, we posit:

Hypothesis 3: *We expect* ***more discretion*** *for responses (a) to* ***riskier*** *applications, (b) from* ***smaller or less mortgage-focused*** *banks, or (c)*

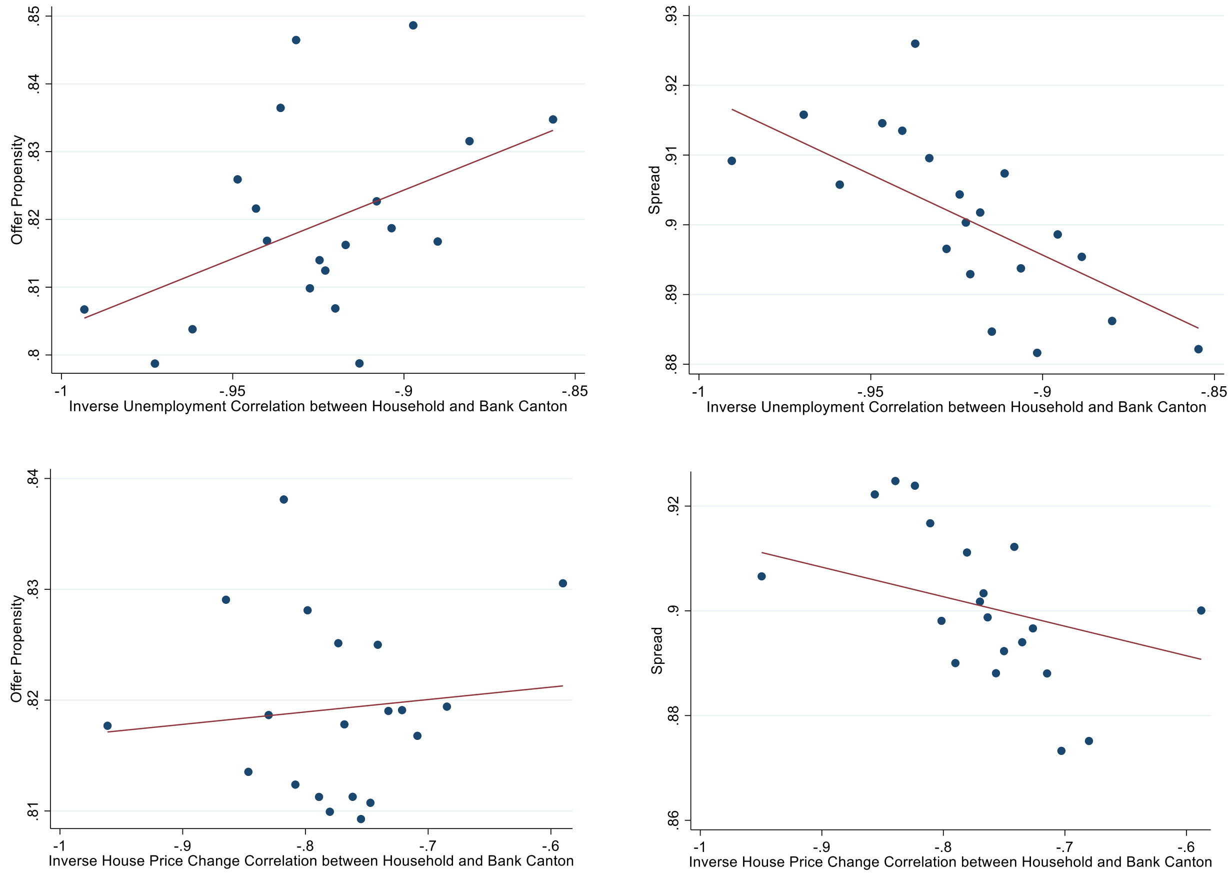

Fig. 2. Bin scatters for offer propensity and pricing against portfolio complementarity
The left panels plot average offer propensities against average values of portfolio complementarity, the right panels plot average spreads offered. Further, while the two upper panels plot these outcomes against unemployment complementarity, the two lower panels plot them against house price change complementarity. As in *Fig. 1*, all panels use 20 equally sized (by the number of bank responses) bins of complementarity values and all panels residualize the averages for the same set of controls as used in our regressions using linear estimation.

submitted with ***less web experience.***

6.2. Strategy on automation

To formalize our ideas on automation vs. discretion, we build on the model of multiplicative heteroscedasticity formulated by Harvey (1976) and used in a bank lending context by amongst others Cerqueiro et al., 2010. The latter find more discretion for loans that are smaller, unsecured or go to smaller and more opaque firms. This can be rationalized by the idea that decisions in these cases are harder to automate well. So, they are more likely to be escalated to (senior) staff. In our context, all loans are mortgages and collateralized. But we expect more discretion on risky applications.

In a first step we estimate the "mean equation", relating the outcomes of interest offer and spread to determinants of interest. Following that, we compute for each response from bank b to household h the squared residual u^2_{hb} as a measure of variation in the outcomes of interest not explained by the mean equation, which we call "Discretion". In step two, the "variance equation" then relates the log of this discretion measure to regressors of interest:

$$\ln\left(u^2_{h,b}\right) = \alpha + \beta X_h + \gamma X_b + \delta(HHI_h) + \theta\left(Complement_{h,b}\right) + \mu\left(Exp_{h,b}\right) + \varepsilon_{h,b} \quad (4)$$

These include again all household characteristics X_h, all bank characteristics X_b, market concentration in the applicant's canton HHI_h and $Complementarity_{h,b}$ between household h's and bank b's canton. In addition, we now include experience $Exp_{h,b}$, measured by the number of responses bank b has already sent out when responding to household h. As before we start by including all bank and household characteristics as expressed in Eq. (4). In subsequent variations, we first replace bank chacteristics with bank fixed effects and then replace also household controls with household group fixed effects. We use the same regressors in both stages.[35]

6.3. Results on automation

As per our *Hypotheses 3a-c,* Table 7 follows largely the same outline as prior tables in terms of controls, and again columns with unequal numbers focus on offer decisions while those with equal numbers focus on pricing decisions. For space reasons the regressions using the offer indicator or pricing themselves as outcome ("mean equations") are relegated to the ***AT5*** and basically confirm the effects of both HHI and risk relevant measures already discussed above. One interesting additional result worth highlighting here is that each 1000 extra responses of experience are found to increase offer propensities by about 1 pp, although the effect of experience on pricing is not robust to different specifications. Building on these mean equations, Table 7 uses as left-hand side variables the log of the squared residual from those mean equations. Following amongst others Cerqueiro et al., 2010, we interpret this as the amount of discretion used in offer and pricing decisions. We

[35] Following Click or tap here to enter text.Harvey (1976)Click or tap here to enter text., we use Maximum Likelihood to improve estimator efficiency.

Table 7
Automating market entry and diversification around a common rule.

	(1) Offer Discretion	(2) Spread Discretion	(3) Offer Discretion	(4) Spread Discretion	(5) Offer Discretion	(6) Spread Discretion
Experience	−0.02**	0.00	0.00	−0.11***	−0.08***	0.07
	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.04)
I(LTV>=67 %)	0.05	0.53***	0.05	0.38***		
	(0.03)	(0.12)	(0.03)	(0.11)		
I(LTV>=80 %)	0.62***	−0.01	0.70***	−0.00		
	(0.04)	(0.11)	(0.04)	(0.11)		
I(LTI>=4.5)	0.21***	0.03	0.24***	0.02		
	(0.04)	(0.12)	(0.04)	(0.10)		
I(LTI>=5.5)	0.56***	0.01	0.62***	0.06		
	(0.04)	(0.16)	(0.05)	(0.16)		
I(New Mortg.=1)	−0.20***	−0.04	−0.25***	−0.02		
	(0.03)	(0.12)	(0.03)	(0.10)		
Ln(Total Assets)	−0.05**	−0.15***				
	(0.02)	(0.04)				
Mortgages/TA	−0.02***	−0.03***				
	(0.00)	(0.01)				
Deposits/TA	0.02***	0.02***				
	(0.00)	(0.01)				
Equity/TA	−0.08***	0.03				
	(0.02)	(0.03)				
HHI	−0.80**	−0.66	−1.25***	−1.15	−1.34***	−0.77
	(0.34)	(0.76)	(0.38)	(0.88)	(0.36)	(0.69)
HP Growth	−1.76***	−0.50	−1.78***	−1.86*	−0.10	0.00
	(0.56)	(1.18)	(0.59)	(1.13)	(0.84)	(1.88)
Number Providers	−0.04***	−0.04**	−0.05***	−0.08***	−0.04***	−0.03*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Unemployment Complementarity	−1.67***	−1.40*	−1.03***	1.25	−1.11***	−0.10
	(0.34)	(0.72)	(0.39)	(0.95)	(0.33)	(0.75)
Constant	−1.61***	−1.80*	−2.29***	−2.28**	−1.99***	−3.12***
	(0.46)	(1.01)	(0.51)	(1.03)	(0.01)	(0.03)
Bank FE	No	No	Yes	Yes	Yes	Yes
HH FE	No	No	No	No	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	No	No

Regressors and specifications follow those in Table 3, but add “Experience” as the number of online mortgage applications (In 1′000) the responding bank has already processed since the platform start in 2008. In the Online Appendix we display the underlying mean equation relating offers and prices to these regressors. Here we display the variance equation relating the log of the squared residual from the mean equation to the regressors of interest. Standard errors in parentheses are robust. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

now discuss the economic magnitudes of the different drivers of interest of this discretion.

Starting with household characteristics, we find that offer decisions have a 62–70 % larger squared residual and hence a 7.9–8.3 % larger residual, which we call discretion, when the LTV ratio exceeds 80 %. Likewise, we observe 4.6–4.9 % more discretion when the LTI ratio exceeds 4.5, and another 7.5–7.9 % when it exceeds 5.5. In addition, pricing decisions contain 6.2–7.3 % more discretion already when the LTV ratio exceeds two-thirds. These findings clearly support our *Hypothesis 3a* whereby decisions on riskier clients tend to be escalated to manual or even senior human staff. By contrast, decisions on safer clients are to a greater extent left to automated choice. This is consistent with the predictions in Petersen and Rajan (1995) whereby banks exert more discretion when lending to more “opaque” firms.

Relatedly, we find 2.2–3.9 % less discretion in decisions for each percent by which the bank has a larger balance sheet. We also find 1.4–1.7 % less discretion for each percentage point of total assets previously invested in mortgages. These two findings confirm our *Hypothesis 3b* whereby banks with more prior mortgage expertise can automate their decision-making to a larger extent. Further, we find less discretion in decisions about applications from more concentrated and more complementary markets. These two findings are in line with those discussed above whereby banks are particularly eager to lend to those markets, and this preference may dominate other considerations sufficiently often that banks decide in a more automated fashion and hence more quickly in these cases. Finally, we observe 1.4–2.8 % less discretion in offer choices for each 1000 responses made before. We cannot confirm that this experience allows banks also to automate their pricing more, but we consider the greater automation of offer decisions as confirming *Hypothesis 3c*.

One might be concerned that the heteroskedastic regression procedure estimates less discretion or more automation for one subgroup than for another merely because the former subgroup contains more observations and therefore exerts more influence on the one rule estimated. To address this concern, ***AT6–8*** repeat our estimations but now estimate respectively bank, calendar year, or experience year specific rules. The tables show robustness of our findings of more discretion for riskier applications, from smaller or less mortgage-specialized banks, for less concentrated markets, or for markets more complementary to those dominating the responder’s portfolio. By contrast, the finding that discretion generally decreases with platform experience loses its robustness, with findings depending on the set of controls used. Increasing automation can allow banks to cut operational costs. Admittedly we do not explicitly observe whether greater automation comes at the cost of more wrong decisions. But the fact that in the setup studied banks dispose of high-quality hard but no soft information suggests to us that decision quality would be unlikely to be better if decisions were made with more discretion. Lastly, we note that automation is not specific to online communication, but is arguably easier in this context where clients do not expect to be talked to regardless of their riskiness.

7. Conclusion

In this paper we have investigated how banks allocate mortgage lending to different regions when a FinTech online platform allows them to lend also to regions where they have no branches. Observing the responses from differently located banks to each household, as well as responses from each bank to differently located households, allows us to remove most if not all biases which could emanate from the selection of different banks by different households.

We find that when responding to an application from a more concentrated market, a bank is more likely to make an offer and in addition willing to lower its price. This may be counter-intuitive *prima facie* as we could have expected higher concentration to allow banks making *less* attractive offers. But more concentrated markets also offer online bidders the chance to get "a foot in the door" in markets with in expectation more attractive future business. For potential borrowers located in such hitherto more concentrated markets, this implies that the availability of an online platform can lead to more and better mortgage offers. We obtained these findings by instrumenting actual changes in cantonal market concentration with the product of a nation-wide shift, namely the shortfall of Big Two lending growth relative to market-wide lending growth, and prior cantonal market shares of the Big Two.

In addition, we find banks to offer about 2 % (1 %) more often and in addition reduce their prices by about 2 bps (1 bps) more if the applicant's canton has a one standard deviation lower unemployment rate (house price change) correlation with the bank's own canton. So the platform allows banks to improve the inter-regional diversification of their mortgage portfolio and hence ceteris paribus improve their risk management following amongst others Quigley and van Order (1991). We deem the risk management benefits from more inter-regional diversification to dominate potential increases in the cost of raising information on more regions, as suggested by Loutskina and Strahan (2011), in the market analyzed. For collateral values here are assessed with the same hedonic models country-wide and information on borrowers are equally reliable for all regions.

Last, we investigate the discretion banks retain around estimated decision rules and interpret it as cases in which decision-making is not yet fully automated or is even escalated to more senior staff. As expected, we find more automation for safer loans, by larger banks, and by banks more specialized in mortgage lending. We also find that discretion decreases, or automation increases, the more online responses the bank has already sent out. This suggests that longer participation with the FinTech online platform can help banks reduce operating costs. Absent a crisis we do not yet know for sure whether such automation increases the potential for erroneous decisions in the sense of under- (or over-) pricing credit risk. But we do observe that banks price in all commonly considered mortgage risk factors such as LTV and LTI ratios, so we have no reason to suspect that banks offer less carefully online.

The key implication of our findings for banks is that they can use online platforms to onboard new profitable clients, to diversify their loan portfolio, and to reduce operating costs. At the same time, the strong bank client stickiness found in Basten and Juelsrud (2023) suggests that in some markets, banks may need more than online banking to onboard a lot of new mortgage clients, with more research and experimentation needed to find the best strategy. From policy-makers' perspective, the enhancement of competition from easier market entry online would overall seem desirable, even if client stickiness means that online competition is no panacea. Desirable seem also online diversification opportunities to the extent to which they exist. Opportunities for greater automation of lending decisions seem also desirable – up to the point where risk management quality a suffers, a point for which we did not yet see evidence in the setup studied but which both banks and policy-makers will need to watch carefully.

CRediT authorship contribution statement

Christoph Basten: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Steven Ongena:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Data availability

The authors do not have permission to share data.

Supplementary materials

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