The Geography of Mortgage Lending in Times of FinTech[$]

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We analyze how banks' inter-regional mortgage allocations change when an online platform enables them to offer to regions where they have no branches. Unique data on responses from different banks to each mortgage application yield three novel findings. First, banks offer more and cheaper credit to borrowers in previously more concentrated markets, identified with quasi-experimental overseas bank losses. Second, banks prefer lending to regions where collateral prices are less correlated with those at home, identified with linguistic differences, or where current prices seem less over-heated. Third, over time offers become more automated, lowering operational costs.

Keywords: Mortgage Lending, Spatial Competition, Credit Risk, Diversification, Automation of Banking, FinTech, Online Pricing

JEL Classification: G2, L1, R3

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1 Introduction

Every mortgage is associated with a specific location in which its collateral is based in a way in which other assets on bank balance sheets are not. This location matters for the lender in at least three ways. First, different regional markets are often characterized by different intensity of competition so that the same bank can earn higher margins in one market than in another. Second, regions matter also for risk management. To start with, collateral prices in one region may be deemed more over-heated than those in another. More importantly, as long as house prices in different regions are at least not perfectly correlated in up- and downturns, lending to one region may improve the diversification of the mortgage portfolio of a bank previously focused on other regions, while yielding smaller or no diversification benefits to a bank already focused on that region to start with. Third, beyond revenue and risk management considerations, different locations may also imply different operational costs, as lending to different locations may give a bank different potential for automation.

These three sets of considerations suggest that banks may have reasons to prefer lending to one location over lending to another. Traditionally however, banks cannot freely choose the location for every mortgage even across the full territory of their banking license, as they can acquire and serve new customers only in those regions in which they already have a sufficiently dense network of branches, adequately trained staff, and are sufficiently known to potential customers. Establishing all of this implies significant initial cost. Relatedly, as researchers we cannot directly attribute the geographical distribution of a bank's lending to its preferences, as part of it may result simply from legacies.

Both for banks, and for us as researchers, things have started to change with the appearance of FinTechs that offer online mortgage platforms where potential borrowers from across the country can apply for a mortgage and potential lenders from across the country can serve them. In this paper we exploit data from the Swiss platform Comparis.ch. Beyond breaking down historical legacies of geography, these data have two other major advantages. First, we observe mortgage applications pre-intermediation and subsequent lender responses and can hence distinguish demand and supply in a way not possible with data on completed contracts or data at even higher levels of aggregation. Second, 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 thus break any endogenous matching of different types of borrowers to different types of lenders. Following pioneering work by Khwaja and Mian (2008), this feat has been achieved more recently by several papers on bank lending to large firms with more than one bank relationship, such as Jimenez et al (2012, 2014). By contrast, it is less common for households to entertain active relationships with several different banks, or at least for researchers to observe relationships with different banks for the same household. Identification of the quality of Khwaja and Mian (2008) has therefore, to our knowledge, been achieved for lending to households only by two papers so far. First, Basten (2019) was the first to exploit the Comparis data analyzed here and found that higher counter-cyclical capital requirements caused more affected banks to raise prices relatively more, and thereby caused a shift of new lending from more to less affected banks. Second, Michelangeli and Sette (2016) obtained responses from different banks to the same household by sending randomized simulated mortgage applications to different banks. Analyzing data on multiple banks' responses to each of 6'920 household mortgage applications made through the Swiss online platform Comparis.ch between 2010 and 2013, we obtain three main sets of findings.

First, banks make more and cheaper offers to applicants from cantons (states) where mortgage lending has so far been more concentrated, allowing them to enter new, more profitable markets, and households to obtain better offers. As an applicant's canton has the same prior concentration for all online bidders, estimates on banks' eagerness to lend there could be biased downward if prior competition was less intense because of unobservables that also reduce banks' current eagerness to lend there. For this reason we exploit quasi-experimental variation in prior market concentration arising from the need for Switzerland's two big universal banks UBS and Credit Suisse (CS) to cut new mortgage lending after hefty losses in the US subprime crisis and subsequent withdrawals from Swiss depositors. In cantons where these two big banks had previously held larger shares of the market this opened up opportunities for competitors offline or online, which in balance reduced prior market concentration. Instrumental variable (IV) results exploiting these events confirm that banks seize the online channel in particular to enter previously more concentrated markets where they can earn the most profitable follow-on business, including through cross-selling given customer switching costs. Results based on our IV strategy are stronger than pure observational correlations, as possible unobservable differences in a location's attractiveness to banks may have affected prior concentration as well as current offer behavior. For clients in previously more concentrated markets, the web platform thus yields more and better offers.

Second, we find that banks seize the online channel in particular to lend more to regions where house price changes are less correlated with those in their home canton and hence in their existing portfolio, as well as to regions where current prices are deemed less over-heated relative to those at home. As past price changes could possibly stem partly from patterns of past lending behavior which characterize also current lending behavior, our baseline estimates instrument past price correlations with linguistic differences and borrower-lender distance in kilometers. This is based on the findings in amongst others Basten and Kpch (2015) whereby house price growth in different regions in Switzerland depends on "supply push" immigration from different source countries: Swiss regions that speak predominantly German (, French, Italian, Romansh) tend to receive more net immigration, resulting in higher house price growth, when Switzerland as a whole receives more net immigration from Germany or Austria (France, Italy, Portugal or Spain), and likewise more distant regions are ceteris paribus affected differently by migration from different source countries depending on their geographical proximity as well as their sectoral specialization. This instrumentation of price correlations, to proxy credit risk correlations, confirms that banks can and do seize the web to improve their portfolio diversification.

Third, we find that cross-sectionally banks automate mortgage lending decisions more for less risky applications as well as when they themselves are larger or more specialized in mortgage lending. More interestingly, we also find that the longer banks have been lending online the more they manage to automate their decision-making, which has the potential to lower banks' operational costs without unduly sacrificing the quality of decision-making. *In addition*, we analyze how much offers extended to literally the same household differ across lenders. We find more dispersion the higher the credit risk, and the lower the expected profitability in that canton.

The remainder of this introduction lays out how our findings contribute to four strands of the existing literature. Following that, Section 2 introduces our hypotheses in the areas of respectively competition, risk management, and automation, as well as on the dispersion of offers received by each household. Section 3 then introduces our data and Section 4 provides more details on our empirical strategy. Section 5 provides our results and Section 6 concludes. The Online Appendix provides useful background information and probes the robustness of our findings to a wide range of methodological variations.

1.1 Contributions to the Existing Literature

With our three main sets of findings, we contribute to four strands of the literature. First, we contribute to the emerging literature on how financial technology or "FinTech" changes financial intermediation. We follow the definition by Thakor (2019) of 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 mostly on the lowering of search costs of matching transacting parties, while economies of scale, cheaper information transmission, and a reduction in verification costs play only a side role here. Buchak et al (2019) by contrast consider only FinTechs simultaneously defined as shadow banks in the sense of non-depository institutions, as their paper seeks to explicitly test to what extent FinTechs' growing role in credit origination is due to technology and to what extent to being regulated differently than traditional banks. We focus on activity rather than on who carries it out, as the same online platform studied here 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] Comparing lending of non-banks with that of banks, Buchak et al find that non-banks do neither offer lower prices nor lend to riskier borrowers, but rather earn larger margins by offering more convenience. In line with this, Fuster et al (2019) also emphasize that FinTechs can earn higher rather than lower margins by addressing market frictions. We focus on banks subject to the same regulation, and show how an online platform can specifically address frictions from geography, with an impact on

[1] This is consistent with the more comprehensive definition by the Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS) as "technologically enabled financial innovation that could result in new business models, applications, *processes*, or products with an associated material effect on financial markets and institutions, and the provision of financial services".

[2] In the years studied Comparis as a non-bank provided an online mortgage platform in Switzerland, while more recently Goldman Sachs as a foreign bank became interested in becoming involved in another Swiss online mortgage platform, and the Swiss bank UBS also considered organizing such 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 respectively, both accessed on October 21, 2019.

competition, risk management and automation. The friction addressed here is that previously borrowers could not borrow from lenders not physically present in their region, which disadvantaged in particular those borrowers located in more concentrated markets. The online platform gives them access to a wider range of possible lenders, which bears some analogies with recent findings in Bartlett et al (2018) on how FinTech has improved access to mortgages for minority groups in the US.

Second, looking beyond *financial* technology, we bring together the recent literature on how the internet changes price setting (see Gorodnichenko and Talavera, 2017, Gorodnichenko et al, 2018, and Cavallo, 2017) with an extant literature on rules or automation vs. discretion. Gorodnichenko and Talavera point out that online sales are characterized by lower frictions of price adjustment, easier search and price comparisons, and a more limited influence of geographical barriers. They then show empirically that this leads to more frequent price adjustments and therefore to faster price convergence in response to nominal exchange rate movements, yet some persistence remains. In the lending setup we study, prices can be adjusted more easily also offline as each client receives an offer customized to his or her particular risk characteristics and possibly willingness to pay. But the lowering of search costs and removal of geographical barriers are likely to matter here as well. We investigate for which cases in particular this greater ease for customers in comparing prices customized to them reduces the degree of discretion.

Third, we contribute to the literature on how distance and technology affect the degree of competition in banking (Petersen and Rajan, 2002; Degryse and Ongena, 2005; Degryse et al, 2009; Eichholtz et al, 2019) with results on how the role of distance is modified as sufficiently standardized bank lending moves to the internet.

Fourth and finally, we contribute to the literature on the effects of regional diversification on bank risks. There is by now an extensive literature that exploited the US interstate bank deregulation as evidenced by Goetz et al (2013, 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 (SD) 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 more specifically on how banks can better diversify specifically their mortgage portfolios, where local knowledge is arguably relatively less important. Further, online lending decisions can still be made by the same central decision-maker, removing the agency problems between bank headquarter and local credit officers that may be associated with larger distance. The online platform analyzed may thus reduce agency costs even beyond the level analyzed by Berger and DeYoung (2004) who saw reductions in distance-related agency costs within US bank holding companies through improvements in information processing and telecommunication.

2 Hypotheses

In this section we develop hypotheses, based on prior literature as well as economic intuition, on how an internet platform can change mortgage lending along the three dimensions of respectively competition, risk management through regional diversification, and automation. *In addition,* we develop a hypothesis on which types of borrowers we expect to attract the most diverse set of offers.

2.1 Hypothesis on Competition

Our main interest is in how banks' online offer behavior responds to how concentrated the total, online plus—more importantly—offline, mortgage market in the applicant's region has been so far. In the basic oligopolistic version of the well-known Monti-Klein model (see e.g. Freixas and Rochet, 2008) banks optimize lending and deposit business separately, with any difference in volumes being lent to or borrowed from the interbank market, and they do so for a single period only. More realistically, clients in retail banking tend to 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. One key reason why customers do not shop around afresh for every banking service are switching costs. Thus Beggs and Klemperer (1992) mention in their pioneering paper on switching costs as one of two examples the effort required to close a transactions account with one bank, open one with another, and transfer all transactions information. Referring more specifically to lending, Sharpe (1990) and the refinement by von Thadden (2004), as well as Chapter 3.6 of Freixas and Rochet (2008), point out that lending requires the bank to make some upfront investment into screening and monitoring the client, which has already been made when the loan needs to be renewed, and may be required even less when the bank has furthermore gained additional information about the client during past interactions. As a new lender would still need to pay these costs and typically pass them through to the borrower, the existing lender can add a markup for new lending. Sharpe (1990) then points out that such a setup "drives banks to lend to new firms at interest rates which initially generate expected losses", expecting that later markup increases make this worthwhile.[3] On these grounds, we expect that online mortgage lending is particularly attractive to banks when it allows them to win a new client in a canton where competition is hitherto more concentrated, because then the bank can expect to acquire more profitable follow-on business. On these grounds we posit:

<u>Hypothesis 1:</u> *Banks have a higher propensity to offer, and offer prices with lower margins, the more concentrated the local mortgage market is so far.*

[3] In line with this, Basten and Mariathasan (2018) find that Swiss banks decided to leave deposit rates non-negative even in times of negative interbank rates. This made the deposit business per se loss-making, yet banks were found to prioritize retaining their deposit clients in the expectation of making profits from them again later.

2.2 Hypotheses on Risk Management

Related to competition, Degryse and Ongena (2005) analyzed also the role of distance between banks and borrowing firms. They found banks to charge higher prices to less distant firms, consistent with similar findings by Petersen and Rajan (2000) and Agarwal and Hauswald (2010). They interpret this as banks exploiting the extra costs to firms from periodically traveling to more distant competitors. To obtain these larger margins, a bank may in return need to maintain a larger network of branches that allow it to be the closest bank to a larger number of customers. Given these findings, we might *prima facie* expect offered lending margins to decrease in distance also in our setup. However, the financing of owner-occupied residential property in Switzerland differs from that of firms along at least two relevant dimensions. First, absent a severe crisis residential mortgage borrowers typically do not need to see their bank after their mortgage initiation, different from markets like the UK where households may wish to take out equity after house price increases, or markets like the US where they want to repay early which is ruled out in Switzerland through prohibitive early repayment fees. Second, as discussed in our introduction, for mortgage lending the distance between bank and borrower matters for bank risk management. While, depending on its sector, a firm whose sales area is struggling economically may often have *some* leeway to sell to other markets so that its ability to repay need not be tied to the economic developments in one particular region only, real estate is by definition immobile and its value therefore intimately tied to economic conditions at its location. Hence we include analyses on the role of lender-borrower distance under the topic of risk management rather than competition.

Ceteris paribus we may expect that at locations more distant from the bank's headquarters house price changes and related mortgage default rates exhibit a lower correlation with those closer to the headquarters, where the bank typically has a higher branch density and a larger share of its existing mortgage portfolio. Then a bank can reduce risks to its mortgage portfolio by allocating more of its new lending to more distant regions. In this vein, Quigly and Van Order (1991) analyzed 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. As a consequence, they suggest that capital requirements associated with mortgage lending should be higher not only when the loan-to-value (LTV) ratio is higher but also when the portfolio is less diversified.

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 sensible 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 Giannetti and Saidi (2019) find an internalization of spill-overs from liquidation of firm loans in more concentrated industries. This by itself would speak in favor of seeking to sufficiently dominate one area in order to internalize and therefore ideally remove that externality. Finally, Agarwal and Hauswald (2010) show that banks find it easier to screen firm lenders located closer to them, which is typically the place where a bank has already done most lending in the past. In the same vein, Eichholtz et al (2019) find US banks add margins increasing in distance when pricing mortgages underlying Commercial Mortgage Backed Securities (CMBS) and interpret their measure of distance as a proxy for less soft information.

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 and find that it does overall reduce bank risk, both when measured as the standard deviation of bank stock returns and when measured by Z-scores or 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 arguments made theoretically by Stein (2000).

In the segment of residential mortgage lending studied here, regulation restricts the maximum loan-to-value (LTV) ratio to 90% and the maximum loan-to-income (LTI) ratio to effectively 6, so that none of the mortgages is 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. Finally, all banks have the same hard information on each customer and no soft information in the sense relevant e.g. in the setup of Eichholtz et al. Therefore the context complies very much with one characterized by Stein (2000) as based fully on hard rather than soft information. 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 more or less positive value to the applicant's postcode area than a bank with less local knowledge. Therefore we expect the diversification motif to dominate and posit:

Hypothesis 2: Banks have a higher propensity to offer, and offer prices with lower margins, when:

(a) House prices in the applicant's canton have historically exhibited a ***lower correlation*** *with those in the bank's home canton.*

(b) Real estate prices in the applicant's canton are deemed ***less over-heated*** *relative to prices in the bank's home canton.*

2.3 Hypotheses on Automation vs. Discretion

Any of the determinants of mortgage pricing discussed in the previous subsections can be effective by automating rules, through a computer or by communicating common policies for staff to follow. Alternatively, if staff retain sufficient leeway they may take into account also other factors. In the context studied, we dispose of all hard information the bank received through the Comparis platform and would therefore expect less heterogeneity in offers than in contexts in which loan officers may dispose of additional soft information. Yet the same information on an applicant's postcode may be interpreted differently by different loan officers or on different days.

An interesting way to formalize our ideas on automation vs. discretion is to build on the model of multiplicative heteroscedasticity formulated by Harvey (1976) and used in a bank lending context by amongst others Cerqueiro et al (2011). The latter find more discretion for loans that are smaller, unsecured or go to smaller and more opaque firms, which can be rationalized by the idea that decisions in these cases are harder to automate well and are hence more likely to be escalated to (senior) staff. In our context, all loans are mortgages and hence all are collateralized, but we expect more discretion in response to riskier applications.

Beyond borrower characteristics, we hypothesize that the amount of discretion is likely to vary also with bank characteristics. In particular, banks that are larger or more specialized in mortgage-lending likely have more observations on which to calibrate automated lending decisions, and may also find it worthwhile to pay a higher fixed cost for fine-tuning such rules.

Both considerations apply to online lending as much as to the offline lending analyzed e.g. by Cerqueiro et al, yet the online channel is to some extent different in that banks will learn only over time how attractive to borrowers they must shape their offers to have them accepted. Overall then we posit:

<u>Hypothesis 3:</u> *We expect **more discretion** for offers that:*

(a) *Respond to applications which appear more **risky**, i.e. applications with higher loan-to-value (LTV), or higher loan-to-income (LTI) ratios, or less standard collateral.*

(b) *Stem from banks which are **smaller or less specialized** in mortgage lending.*

(c) *Are submitted when banks have yet accumulated **less web experience.***

2.4 Hypothesis on the Dispersion of Offers within each Household

Above we have connected the characteristics of responses to those of banks, those of applying households, and those of their interaction. But given that we observe for each household up to 10, more often up to 7, and on average a bit over 4 responses, another issue of relevance is how different these responses are. In the existing literature, both Gurun et al (2016) and Bhutta et al (2019) have demonstrated that the same (type of) borrower may end up paying different prices to different lenders. Gurun et al relate price dispersion to lenders' advertising and borrowers' deemed sophistication, while Bhutta et al relate it to borrower risk and interpret this as reflecting not only different credit risk premiums but also differences in borrower sophistication and negotiation ability.

In our context, all applicants use by definition the same channel to compare offers from different lenders. In that setup, if in the extreme all banks followed exactly the same rules, a household might as well just talk to any single bank rather than paying to obtain multiple responses. A priori this is more likely for applications that according to the usually considered measures such as LTV and LTI ratios are safe and are thus likely to be attractive to all banks, whereas higher risks might still be attractive for some banks, e.g. when they are based in cantons where house prices are historically less highly correlated with those in the bank's home canton, but less attractive for others. On these grounds we posit:

<u>*Hypothesis 4:*</u> *Spreads are more dispersed for households with higher LTV or LTI ratios.*

Having developed these hypotheses, let us now consider how to operationalize tests of them.

3 Data and Institutional Background

3.1 Data Sources

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. For reasons of data quality, we focus on 2010-13. The resulting data are unique and offer at least four advantages for our analysis. First, we separately observe demand and supply. Second, banks in their operation and we analyzing them can pin down the effects of banks' 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. And fourth, we observe 100% of the information each bank also has on each client. Bank decisions cannot be based on prior personal interaction, so our analyses cannot be biased by the use of soft information.

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, such as Jimenez et al (2012) and Jimenez et al (2014). By 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 the key role of mortgage markets in causing 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. To our knowledge the first paper to observe how different banks respond to the same mortgage borrower is Basten (2019) who uses the same Comparis 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. 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 (2019) and Basten and Mariathasan (2017). 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.[4] Prices offered here are indeed a key dimension along which banks can influence how many mortgage contracts they conclude each period. Thus Basten (2019) shows, using the same data, how banks more affected by higher capital requirements increase offered mortgage rates more and thereafter end up with lower

[4] As the majority of offers consist of only 1 tranche, and as offers with several tranches have the majority of the amount offered in the 1st tranche, focusing on the 1st tranche only rather than on weighted averages across all up to 3 tranches yields qualitatively the same results.

growth rates in their mortgage volumes. 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. On the basis of the same hedonic quality adjustments they also compute house price indices for different quality segments from which we compute year-on-year house price growth rates. Furthermore, FPRE also estimates the extent to which current average house prices are "over-heated" in the sense of exceeding those prices deemed sustainable on the grounds of fundamental factors like incomes, rents and population growth (FPRE and BAK Basel, 2009). Banks who are clients of FPRE or at least read their publications will be aware of their estimates explicitly, those who are not may be using other measures which are likely at least positively correlated with the FPRE estimates of over-heating.[5]

3.2 Descriptive Statistics

Overall we start with 6'914 applications, which attract a total of 25'125 responses. 20'583 of these are offers and 4'542 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 2'000'000, with an average value of about CHF 600'000. The LTV ratio varied between 15% and 90%, with an average value of about 65%. Here the maximum is shaped by the fact that for any mortgage violating the self-regulatory requirement of at least 10% of "hard equity" 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 an average of close to CHF 170'000, wealth including pension fund wealth reached an average close to CHF 500'000, and average age was 46 years.

[5] We focus here on the measure for single-family homes (SFH). FPRE computes an analogous measure for apartments which yields very similar results in our regressions.

Next, *Panel (B)* gives the key regional characteristics. The Herfindahl-Hirschmann Index (HHI) of market concentration for new mortgage lending ranges across the 26 cantons between 0.09 and 0.57, with a mean of 0.18 and a standard deviation (SD) of 0.05. An alternative measure computed with the levels of mortgages on bank balance sheets, rather than year-on-year differences, has a similar mean of 0.19 and the same SD, but ranges only between 0.12 and 0.49, as it is by definition more persistent. The number of online providers varies across cantons between 4 and 14, with an average close to 12, while the multi-market contact (MMC) measure of how many competitors in a canton a bank meets on average in how many other cantons ranges between 0.05 and 0.40. The optional control variable of SFH price growth reaches an average of close to 4% p.a. More importantly, our instrument for the impact of big banks' mortgage retreat on the HHI, namely their prior cantonal mortgage market share, varies between 9% and 57%, while their share of branches in 2007 ranges between 6% and 33%.

Looking at bank characteristics 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. Between about 40% and 91% of these, and on average 70% of them are invested in mortgages, which reflects the general focus of Swiss retail banks on mortgage lending, see also *Basten and Mariathasan (2018)*. On the liability side, the most important position for most banks are deposits, with a range between about 17% and 66% and an average size of 48%. The capital ratio ranged between 4.72% and 11.33% and averaged 7.25% of total assets. When sending out their responses, banks had accumulated experience with answering mortgage applications online through Comparis.ch for between 0 and 69 months. The maximum is reached for responses submitted in the last months of our sample, September or October 2013, by banks participating since the platform start in early 2008. The *average* response in the sample is sent out by banks that at that point in time had a bit over 34 months or close to 3 years of experience of bidding for mortgages through Comparis.ch.

Panel (D) finally gives the key characteristics of bank-household interactions. The inter-cantonal correlation of house price changes achieves a mean of 77% with a SD of 19%, but goes as low as 15%. Current prices in applicants' cantons are deemed between 75% and 208% as over-heated as in the responding bank's home canton. 22% of responses are sent to a canton where the dominant language differs from that in the bank's home canton. On these grounds the average response is sent to an applicant situated 110km or 1.3 hours away from the bank. The average household receives a bit over four different responses. On average this takes about 97 hours or about 4 days, although a bit over half of all responses arrive already within 48 hours. About 82% of all responses are offers. The rate fixation period ranges between 0.25 years for mortgages where the rate adjusts to the CHF Libor interbank rate every 3 months and 10 years. The average of 7.4 years reflects that 10 years is the most common fixation period, as discussed in more detail in Basten et al (2017). The average rate offered amounts to 2.16%, which implies an average spread above the swap rate for the same fixation period of 90 basis points (bp). Yet the spread varies between 40 and 152 bps, so banks' eagerness to win a deal varies significantly.

4.3 Representativeness

An important question when analyzing data from online lending is how representative these are of the offline market. To start with, *Table 6* in our Online Appendix presents the distribution of all 6'920 mortgage applications submitted between 2010 and 2013 across the 26 cantons, in Column (1) in terms of absolute numbers and in Column (2) in percent. In Column (3) it then compares that distribution with the percentage of new mortgage borrowers in the Swiss Household Panel (SHP) by the Swiss Federal Office of Statistics stemming from each of the 26 cantons. A new mortgage borrower is defined as a household who first transitions from renter to home owner in 2008-13[6] and so has mortgage debt in 2014. Finally, Column (4) presents the distribution of cantons of all existing mortgages on bank balance sheets as of 2013. Overall, we find that the distribution of applications is quite representative of the market as a whole and is not for example biased toward more urban areas or toward any of Switzerland's four language regions.

Likewise, *Table 7* contrasts the geographical distribution of the headquarters of the 27 banks in our sample with that of the universe of Swiss retail banks used in *Basten and Mariathasan (2018)*. That paper starts out from the universe of all Swiss banks and then zooms in on the 50 retail banks by following the supervisor's definition of a retail bank as one that earns at least 55% of its income either as net interest income or as loan fees. Of course the distribution of banks is less smooth in our sample than that of households given only 27 banks in total. Yet we observe that the sample includes banks from across the country with greater numbers of banks stemming from the most populated cantons Zurich, St. Gallen and Berne as well as Aargau and Basel. But it includes also representatives from French-speaking Geneva, Valais and Vaud, as well as from Italian-speaking Ticino. Overall this makes us confident that the findings presented below are representative of bank behavior across all of Switzerland. Given the extreme heterogeneity of Switzerland in terms of language, religion, topography and urbanization, it may furthermore be argued that despite the limited size of the country, behavior is also representative of that in larger countries.

Finally, *Table 8* looks beyond geography. Panel A compares the characteristics of households in our sample to those of households in the Swiss Household Panel (SHP) who recently acquired real estate. Panel B compares mortgage risk characteristics in our sample to those reported in the SNB Financial Stability Report 2014. Panel C finally compares the key characteristics of banks in our sample to those reported for all retail banks in Basten and Mariathasan (2018). In all three cases, we report all characteristics that are available both in our sample and reported in the respective benchmark. Column (1) always reports the mean value, and in brackets the standard error, in our sample, and Column (2) those in the benchmark—except for Panel B as SNB (2014) does not report standard errors. Panel A thus shows that households in our sample have virtually the same average age, but a higher household

[6] We start in 2008 to make the distribution sufficiently representative.

income. While the difference is not significant statistically, we deem it is significant economically. We do not see any obvious way in which this would distort the results of our bank-focused analyses, yet this difference is to be kept in mind. For the key risk characteristics of households displayed in Panel B, the best available benchmark for this is SNB (2014). Based on a bank survey that covers the 25 largest mortgage lenders and thereby 80% of the market, it reports that 7% of mortgages start with an LTV value above 80%, which corresponds very closely to the value of 8% in our sample. Furthermore, they report 18% of households starting with a Payment to Income (PTI) ratio above 33%, where the annual payment is computed as 5% of the loan for interest plus 1% for amortization plus 1% of the loan for house maintenance. When we multiply our LTI ratios with 0.07, we find that 17% of households start out with a PTI ratio in excess of 1/3. While we cannot formally compare the two percentages with a t-test for lack of data on standard deviations in the SNB data, the differences of 1 percentage point each suggest that from the household side the Comparis data are overall representative of the offline market, featuring neither a flight of particularly risky households from offline to online lending nor a particular eagerness by particularly safe households to obtain better conditions online. Finally, Panel C shows that banks in our sample have a very similar risk-weighted capital ratio, but tend to be somewhat smaller and more deposit-financed. This likely reflects the fact that for larger banks it is more easily worthwhile starting their own online platform for mortgage lending or expanding their offline branch network, while the Comparis platform is particularly attractive for smaller banks.

4 Empirical Strategy

We organize our analyses around the areas covered in our hypothesis section above: competition, risk management, and automation, as well as the dispersion of offers within each household. As a general matter, we cluster standard errors by bank * household zipcode area. While 26 banks only would provide too few and too unequally sized clusters, this yields 7'464 clusters, the size of which ranges from 1 to 55 and has a SD/Mean of 0.95. In alternative versions available on request we have instead clustered by household, or by bank*zipcode*year and none of this does materially change our results. Interacting each bank with each household zipcode and hence each household location however seems to best fit the content of our analyses.

4.1 Strategy on Competition

Our key measure of the concentration of cantonal mortgage markets is the Herfindahl-Hirschmann Index (HHI), i.e. the sum of squared market shares, for the year-on-year growth in cantonal mortgage volumes.[7] Based on observations of mortgage levels per canton and bank, we approximate the growth in new lending with the year-on-year difference in levels. To be sure, this difference will depend on new lending minus repayments. However, due to tax incentives annual repayments in Switzerland are normally chosen as the minimum required by regulation, which requires households to reduce their loan-to-value (LTV) ratio to two-thirds within 15 years of purchase. By contrast, when a mortgage needs to be refinanced at maturity, it will remain accounted for in the same canton, as volumes are accounted for by the canton in which the collateral is based. In a few cases in which banks have low volumes in certain cantons, some year-on-year differences are negative. For our baseline we replace negative growth rates with zero growth rates to ensure that all HHI values are bounded between zero and one. In one robustness check available on request, we include also negative values. In another, we compute the HHI based on levels rather than differences, which will reflect the concentration of new lending in the past *few* years rather than in the most recent year only. Both methods yield qualitatively the same result.

More importantly, when analyzing the effect of prior market concentration in the applicant's canton, we can — other than in the analyses on inter-cantonal house price correlations or relative house price over-heating discussed below — not exploit variation within the same applicant. It is then possible that different banks' prior presence as well as current offer behavior are influenced by the same unobservable. In that case, our estimates whereby banks are more eager to lend to previously more concentrated cantonal markets constitute only a lower bound on the true effect, for they might be even

[7] Not only do data on annual mortgage volumes by bank and region not exist for regions more granular than the 26 cantons, but cantons are also considered separate but entire markets by Swiss practitioners. This is so because in particular many cantonal banks have mandates restricting which cantons (often their home plus directly neighboring ones) they can lend to.

more eager to lend there keeping fixed unobserved disadvantages of that region which might also have reduced banks' prior offline presence and thereby led to a more concentrated market.

To address this concern, we instrument the concentration of new lending in 2010 with the market shares of the two big universal banks UBS and Credit Suisse (CS) in 2009, both of whom had to drastically cut new mortgage lending exactly in the years we study due to losses in the US subprime crisis and subsequent withdrawals of Swiss deposits. The episode and its exogeneity to Swiss mortgage markets is discussed in more detail in Brown et al (2019) as well as in Blickle (2018). While Brown et al analyze which types of households were how quick to withdraw deposits from the big banks, Blickle exploits the fact 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 and enabled it to increase their mortgage lending, while outflows from UBS branches that had no Raiffeisen bank nearby would typically have flown to other banks. Here we go one step back and focus on the fact that, while selected Raiffeisen banks could lend *more* following the deposit inflows, UBS and CS had to lend *less* following their deposit outflows. While the opportunities of the two big banks to borrow without collateral from other banks which had not experienced overseas losses or had even received increased deposit inflows were limited, the Swiss National Bank (SNB) orchestrated an opportunity for them to issue additional covered bonds and thereby borrow against collateral from the other banks through the so-called "Limmat transactions" in 2008 and 2009.[8] 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.[9] Yet given capital constraints new lending was not a priority in the following years, especially for mortgages where the relationship component was arguably less important than for much corporate lending.

Relevant for our purposes is the fact that the same reduction in UBS' and CS' mortgage lending had, in the style of Bartik instruments, a relatively larger impact on cantons in which these two big banks had previously been serving a larger share of the market. Firstly, clients seeking to refinance a mortgage previously taken out with them will first of all ask for refinancing conditions with their existing lender. Secondly, also new clients will be more likely to inquire with those banks from whom many of their neighbors have borrowed in recent years, and which have more branches in the area. When these two banks then rejected more applications or offered only unattractive prices, this opened up opportunities for competitors with previously smaller market shares and thereby reduced the HHI measure of market concentration. In our Online Appendix we present, and discuss in the Results section, the corresponding first stage regressions and a variation where we instrument market concentration with big banks' prior share of branches instead of their share of prior lending.

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

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

We also present simple OLS regressions, as well as OLS regressions which control also for a measure of multi-market contact (MMC) of the banks offering in the applicant's canton, as used in Degryse and Ongena (2007). This follows Edwards' (1955) idea 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 though, Park and Penacchi (2008) find that the presence of more multi-market banks can *promote* more competitive behavior. So we need to look at the data to find out. Either way, the MMC measure for each canton sums the number of bank pairs present after weighting each pair by the number of other cantons in which this pair does also 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 $MMC_j = \frac{2}{26 f_j (f_j - 1)} \sum_{k=1}^{180} \sum_{l=k+1}^{180} a_{kl} D_{kj} D_{lj}$. Overall the resulting MMC measure ranges between 4.6% and 40.5% and reaches an average of 7.5%.

4.2 Strategy on Risk Management

As we do not directly observe inter-cantonal correlations between expected losses (EL), we use that apart from the interest rate level, which is the same across the country, a key determinant of losses are local economic growth rates, which are reflected also in house prices and hence collateral values. Thus our main measure of how well a given mortgage would complement the bank's existing portfolio is the correlation between past house price changes in the applicant's canton with the average canton to which the bank has lent in the past, which for the majority of regionally limited banks in our sample is close to that with the bank's home canton.

Past correlations are based on year-on-year growth rates in a house price index for medium-quality apartment prices since 1985 from FPRE consultants, but growth rates on low or high quality apartments or single-family homes yield very similar regression results. These correlations are all positive: Within a country as small as Switzerland that is 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 the summary statistics show that as different cantons specialize in different economic sectors and tend to receive their majority of net immigrants from different countries, some inter-cantonal correlations are as low as 0.15, which does provide a good degree of diversification.

While in the above analyses the same market is equally competitive for all banks responding to the same applicant, the same applicant may differently complement each bank's existing mortgage portfolio for risk management purposes, allowing us to analyze banks' consideration of risk relevant factors more by way of within-household comparisons. Furthermore, for risk management purposes what matters are arguably correlations of credit risk between different components of the portfolio and less what exactly *causes* banks to complement their portfolio with one loan but not with another.

Nonetheless, we cannot exclude that past house price correlations were partly caused by bank lending behavior, which — to the extent to which it is persistent — we might be picking up also in our analyses of current bank responses, in which case there could exist some form of reverse causality from (persistent components of) bank lending behavior to house price correlations. Therefore our baseline analyses instrument past house price correlations with a determinant that is plausibly not caused by bank behavior. In particular, we use an indicator for whether the bank's headquarters is based in another of Switzerland's four language areas German, French, Italian or Romansh than the applying household. The idea is to reflect specifically different migration patterns. Thus Basten and Koch (2015) have shown that when economic growth is lower in for example Germany (France, Italy), then for any level of economic growth in Switzerland this triggers more net "supply-push" migration into Switzerland as a whole, and thereby has a larger effect on net migration into Swiss regions with traditionally more migrants from Germany (France, Italy) than others. As a result these regions experience higher rent growth and as a result of that higher house price growth, regardless of how willing banks are to lend to those regions. One of the key determinants of migration patterns is a region's majority language, which does arguably not depend on recent or current bank lending behavior.

In a further robustness check in our Online Appendix, we add as a second exogenous instrument of house price correlations the distance between the two locations in 100km. The underlying idea is that house price correlations will likely depend also on regional economic specialization patterns, as e.g. tourist resorts in the mountains like St. Moritz tend to attract different sets of migrants than the financial centre of Zurich or the pharmaceutical industry of Basel. On average, specialization patterns tend to be more different the more distant from each other are the regions of applying household and bank.

4.3 Strategy on Automation vs. Discretion

Following analyses on both competition and risk management, we explore to what extent the responses to the factors discussed above are automated, to what extent we observe prices to fluctuate around the values predicted by these factors, and whether this extent differs between different types of responses. To do so, we implement regression models with multiplicative heteroscedasticity as introduced by Harvey (1976). In a two-step procedure, he suggests to first estimate the relationship between regressors and outcomes of interest, in our context regressing offered spreads on competition intensity and regional characteristics as explained above. In a second step, we can then compute for each observation the residual variation u_i^2 not explained by our model and regress its log on our regressors of interest. In our case, we start with the full set of household and bank characteristics used also in the analyses discussed above, and add indicators for whether the applicant wishes to finance a single-family home (SFH) or a less standard type of real estate (villa, multi-family-home, or holiday home) rather than an apartment. Following that, we look first at the measures of market concentration discussed above, and then at the same risk measures as discussed above. Then we analyze in addition how the extent of discretion relates respectively to how fast the response was sent and to the number of months for which the bank has already been offering mortgages online. Our baseline estimates are computed based on the same pricing model for all banks. In our Online Appendix, we use instead a a separate pricing model for each bank by interacting each model parameter with each bank fixed effect, and show that this yields qualitatively the same estimates for the determinants of the amount of discretion.[10]

4.4 Strategy to Analyze the Dispersion of Offers within each Household

As we observe responses from multiple banks to each application, another dimension of interest is to what extent responses are similar and to what extent they differ. Each application receives between 1 and 10 and on average a bit over 4 responses. When we rank the first 7 responses, given that receiving 8 or 9 is rare, in ascending order by spread, average spreads are respectively 79bps, 90bps, 95bps, 99bps, 103bps, 107bps, 108bps. Gurun et al (2016) measure dispersion as the difference between the 95th and 5th percentiles of "mortgage expensiveness", defined as the residual a borrower pays relative to the mean price paid by a borrower *with the same characteristics*. As we focus on offers sent to *literally* the same household, we observe only 2-4 offers for many households so that inter-percentile differences would arguably be too much driven by outliers. Therefore we follow instead Bhutta et al (2019) and measure dispersion as the SD of prices each household is offered. For *Table 5*, we thus compute for each household the SD of spreads in basis points, as well as the SD in percent of the mean spread, and analyze which application characteristics this varies with.

4.5 Strategy to Account for Possible Selectiveness of Prices Offered

So far we have discussed banks' decision whether to make an offer and at what price as if these two choices were independent. However, if for example a bank that is hesitant to lend to high-LTV clients decides not to offer at all to clients with LTV ratios above 90%, then estimates of the surcharge it requires for any LTV ratio above 80% will under-estimate the bank's aversion to higher LTV ratios, because for applications with LTV ratios above 90% we do not observe any pricing response. With a view to how the online platform improves the attractiveness of offers received by applicants, or how it allows banks to contract mortgages which better complement their existing portfolios in terms of risk management, this arguably does not matter: An offer never made helps households or banks as little as one extended at a higher price than those extended by competitors, if it will not be accepted anyway.[11]

[10] Following Harvey (1976), we use Maximum Likelihood rather than two-step estimation to improve estimator efficiency.

[11] While we do not directly see whether indeed a cheaper offer is ceteris paribus more likely to be accepted, even if this would seem plausible, findings in Basten (2019) using the same data confirm that it is: He shows that banks which raised prices relatively more in response to higher capital requirements then had lower mortgage growth on their balance sheet.

However, in the presence of such selection, pricing responses to different factors of interest do at least under-estimate banks' true view of these factors. To account for such possible sample selection bias, we follow Heckman (1979) and estimate first a *selection equation*, in which we regress an indicator for whether the bank responds with an offer on the same set of variables of interest in our pricing regressions, plus additionally a variable which plausibly affects the offer but not the pricing dimension (*exclusion restriction*). Following that, our *outcome equation* repeats our pricing estimations but controls for the estimated propensity of observing an offer.

For the variable that plausibly affects offer propensities but not pricing, we use an indicator for whether an application and the response are sent out in the 2nd rather than the 1st half of a calendar year. This is based on the idea that many banks may set annual targets for their overall volume of mortgage lending and deny more often when upon receiving an application they are already closer to or even beyond reaching their annual target. By contrast, offered prices are arguably chosen with reference to prevailing refinancing costs, credit risks, and competition, which need not differ significantly between the 1st and 2nd half of the year. While we cannot formally test whether the month of the year does really not affect pricing, the approach can yet give us some confidence that offers never made would not have yielded very different effects on the pricing than the offers actually made and covered in our baseline analyses.[12]

[12] In the regressions in which we include a dummy for whether a response was sent in months 7-12 rather than in months 1-6, we do not control for year*month fixed effects.

5 Results

Table 2 presents our results on Competition, *Table 3* those on risk management through the geographical allocation of mortgage lending, and *Table 4* on the extent to which banks' choices are automated. In addition, *Table 5* analyses which types of applications attract a more diverse set of responses. In the Online Appendix, we address in *Table 6* the geographical representativeness of households, in *Table 7* that of banks, and in *Table 8* the non-geographical representativeness of both households and banks. Following that, *Table 9* presents the first stage regressions underlying our baseline competition analyses (*Table 2*), *Table 10* uses as alternative instrument the two big banks' share of branches rather than their prior share of mortgage lending, and *Table 11* presents for comparison results on competition without an instrument, while *Table 12* uses HHI computed with mortgage level shares rather than mortgage difference shares and additionally includes the Multi-Market Contact (MMC) measure. Next, *Table 13* presents the first-stage regressions underlying *Table 3* and *Table 14* presents a variation that instruments price correlations with distance in addition to language mismatch, while *Table 15* provides for comparison the estimates obtained when instrumenting neither price correlations nor HHI. Finally, *Table 16* investigates determinants of discretion when rules are allowed to be bank-specific, while *Table 17* investigates how our results on pricing change when accounting for possible selectiveness.

We now start with general discussions relevant for all of our areas studied, before discussing results more specifically on competition, risk management relevant factors, automation, and offer dispersion. In all analyses on the role of respectively competition and risk management relevant factors, uneven column numbers show the results for the binary outcome offer vs. rejection using probit regressions on all 25'125 responses. Equal column numbers then show those for the continuous outcome pricing using OLS regressions on all 20'583 offers. The tables always show the regressors of specific interest in those tables at the top, followed first by key household characteristics and then by key bank characteristics.

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 threshold values reflect frequent practice in the market[13] and for LTV ratios are identical to those thresholds 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 2019). 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

[13] In particular, banks deem applicants more risky 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 values used in regulation in other countries, such as the UK. Other, similar LTI values yield qualitatively the same results.

statistically significant effect on our outcomes of interest after controlling for the indicators displayed here. Furthermore, 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 the household's wealth (including 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 on the regressors displayed here.

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. Interestingly, the about 50% of applications asking for banks to refinance their mortgage, rather than to finance their initial purchase, tend to receive fewer offers, but when receiving one get better prices, even after controlling for the meanwhile typically lower LTV ratio and possibly higher incomes. This can be explained by the fact that household seeking a refinancing has already had his real estate screened and approved at least once by another bank and furthermore will have been servicing the mortgage already for a while.

When we focus instead on 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 more competitive prices. One plausible explanation of this finding, beyond risk management, is a 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 depends less on selling mortgages also through the online channel. Another is that in contrast to the second most important source of funding for Swiss commercial banks, covered bonds, deposits are typically thought to have shorter effective 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. Finally, banks that are better capitalized tend to charge higher prices, possibly reflecting the fact that a larger fraction of funding raised through equity is typically thought to imply (more bank safety in crisis times but also) higher marginal costs for each unit of lending. After this general discussion on the effects of our main control variables, demonstrating the validity of our setup, let us now turn to our key regressors of interest.

5.1 Results on Competition

Table 2 looks at banks' responses to the intensity of mortgage supply competition in the canton of the applying household. Our key regressor of interest here is the HHI, which is defined to range between 0 in the case of perfect competition and 1 in the case of a pure monopoly. Summary statistics in *Table 1* reveal that in the 26 cantons studied it ranges between 0.05 and 0.57, reflecting the heterogeneity of cantonal markets, and amounts to 0.18 on average. The analogous measure computed with mortgage levels rather than growth ranges only between 0.12 and 0.49, as it is a more persistent measure, but its average is only 1 percentage point higher. In this context, *Table 2* tells us that each extra percentage point of concentration raises banks' offer propensity by between 1.8% and 4%, and conditional on making an offer induces banks to quote a price which is ceteris paribus between 1.38% and 1.89% lower. This is based on instrumenting HHI with the two big banks' mortgage market shares in 2009, which ranged between 9% at the lower end and a striking 57% at the upper end. As first-stage estimates in *Table 9* tell us, each additional percentage point of prior mortgage market share allocated to one of the two big banks is associated with a reduction of the HHI measure by 13-14% when these two big banks had to cut lending following overseas losses and domestic deposit losses. All first-stage regressions exhibit F statistics far above 10, showing that we always dispose of a strong instrument.

When we instrument growth-based HHI with banks' share of branches (currently available only for 2006, i.e. 4 years before the start of the response level data analyzed), displayed in *Table 10*, results are qualitatively confirmed, although effects on offer propensity are not statistically significant here and effects on pricing a bit lower, ranging between 0.85 and 1.17% per percentage point of market concentration. *Table 11* in the Online Appendix shows the same specification without instrument HHI, while *Table 12* does furthermore replace the growth-based with levels-based HHI and controls also (non-causally) for the MMC measure. Both yield significantly smaller estimates, ranging between 0.58 and 1.14 for the outcome offer propensity and between minus 0.34 and 0.54 for pricing. This confirms our argument in the Emprical Strategy section that non-causal estimates on banks' responses to competition will be biased toward zero if the same unobservable canton attractiveness (unattractiveness) caused more (less) competition in the offline market and causes banks to bid more (less) eagerly now. Regardless of which version we focus on, however these findings confirm our *Hypothesis 1* above.

Looking at our set of competition-specific control variables, we also see that each extra competitor also bidding online for clients in the applicant's canton is, as we would expect, associated with a higher offer propensity and lower prices, although these effects are both small after controlling for everything else. Perhaps more interestingly, we find that banks are between 1.8% and 2.5% less likely to make an offer, and if making one demand between 0.17 and 0.82% higher rates for each extra percentage point by which house prices have been growing in the applicant's region in the year before, which may be taken to imply greater risk of house price over-heating, subsequent house price collapse, and hence more credit risk for the bank. We shall investigate the risk dimension in more detail below, but already control for house price growth here, as recent price growth may also be associated with recent changes in competition intensity.

Finally, *Table 12* in our Online Appendix controls also for the MMC measure, which expresses how many other competitors a bank meets in this canton, times the average number of other cantons in which they also encounter each other. Our regressions here find that banks encountering more competitors which they meet also elsewhere are more likely to offer also here and do so at ceteris paribus lower prices. This is more in line with the findings in line with the original "linked oligopoly" hypothesis by Edwards (1955) rather than with the findings of Park and Penacchi (2008) or those of Degryse and Ongena (2007) whereby banks seize each opportunity to compete, than with the original "linked oligopoly" hypothesis by Edwards (1955).

One implication of our results is that the increasing use of online platforms increases competition. It is interesting to look at this also in the context of the model by Hauswald and Marquez (2003), who emphasize how information technology more widely can increase competition when it levels the playing field between banks with more and banks with less private information, but can decrease competition when allowing more informed banks to make even better use of their informational advantage. The setup we have studied here is clearly one in which private information is, as we have argued above, less relevant. When this is different, e.g. for the case of less standardized collateral the value of which can be predicted with less certainty by hedonic models, outsiders entering a market through the online channel would need to worry about Adverse Selection. In line with this, the platform studied focuses on the more standardized part of mortgage lending, and our results confirmed that the less the collateral is standardized the less are banks willing to automate their decision-making.

5.2 Results on Risk Management

As discussed in our hypothesis section above, the online platform allows banks to more freely choose which regions to lend to on the basis of different intensities of competition, but also in view of differences in credit risk. On these grounds, *Table 3* follows *Table 2* in displaying in uneven columns the results for the outcome offer propensity and in even columns our results for the outcome price. Offer being a binary variable, we estimate results for the columns with uneven numbers with Instrumental Variable (IV) probit, those for columns with even numbers with regular IV regressions. In particular, past price correlations between the bank's and the applicant's canton are instrumented with an indicator for language mismatch and with distance in 100km. Columns 1-2 control only for household and bank characteristics, while 3-4 add in addition a measure of how over-heated house prices are deemed in the applicant's canton relative to those in the bank's own canton. Following that, 5-6 add in addition the two measures of competition intensity from *Table 2*, and like there instrument the Herfindahl-Hirschmann Index (HHI) with the two big banks' mortgage market share in 2009.

On these grounds, *Table 3* shows that banks' propensity to make an offer to a region where collateral price changes are 100% correlated with that in their home turf is between 3.6% and 4.5% lower than for a region where prices are uncorrelated with those in their home turf. For a difference of 1 SD of the correlation variable or 19% (see *Table 1*), this implies a change in the offer propensity by about 0.7-0.9%. At the same time, even conditional on extending an offer, a 1SD higher correlation appears to motivate banks, ceteris paribus, to demand a risk premium which is between about 10 and 20 basis points higher, which following the results in Basten (2019) makes it significantly less likely that this offer is accepted and thereby does likely affect the subsequent composition of the bank's portfolio. At the same time, the row's second line shows that a 1SD or 17pp more pronounced extent of relative house price over-heating in the applicant's canton *is associated with* a 0.1% lower offer propensity and an about 3.54bp higher risk premium.

In our Online Appendix, *Table 13* shows the corresponding first stage regressions. It confirms that, depending on the set of controls included, house price changes in the applicant's and the bank's own canton are between 15 and 19% percentage points lower when the two are based in different language regions and this first-stage relationship is always statistically significant at least at the 1% significance level and exhibits F statistics far above the conventional threshold of 10. Following that, the Online Appendix displays for robustness in *Table 14* also a variation of *Table 3* in which house price correlations are instrumented with distance in addition to the language mismatch indicator. Here effects on offer propensities are not statistically significant, but those on prices are positive and statistically significant here as well, albeit smaller. Just for comparison, *Table 15* shows the corresponding results obtained when instrumenting neither price correlations nor HHI. Interestingly, here effects of house price correlations are significantly smaller, showing that instrumenting price correlations does indeed make a difference. More importantly though, all estimates have the same sign and significane, so these as well as the other tables just discussed do overall confirm *Hypothesis 2* whereby banks can and do exploit the online channel to improve the diversification of their portfolio.

5.3 Results on Automation vs. Discretion

After exploiting extensively how banks' offering and pricing vary with competition and risk management considerations, the question arises to what extent outcome variation remains unexplained by these factors and whether that extent does again vary systematically, i.e. whether we have multiplicative heteroscedasticity of standard errors as formalized in Harvey (1976).

In that vein, *Table 4* shows in Columns 1, 3 and 5 the results of the *mean equation* regressing offered spreads on different sets of regressors. Columns 2, 4 and 6 then show the results of estimating the corresponding *variance equation*. It takes the log of the outcome variance unexplained in the mean equation and regresses it on independent variables of interest. To start with, we see here that the pricing equations reaches an R2 of 27-28%. This is significantly higher than for example in Petersen and Rajan (2002), where the R2 from analyzing what determines interest rates on business loans reaches merely 17-18%. The likely reason is that they analyze lending to small businesses, in which loan officers take into account a good deal of soft information, whereas in the setup analyzed here banks have only the hard information we have as well.

Yet, our R2 is by no means close to 100%. In fact, our Columns 2, 4 and 6 show that the amount of rate variation which our model cannot explain does vary systematically with a number of regressors of interest. Starting with household characteristics, we find throughout all columns that when the applicant's LTV ratio exceeds two-thirds, then the squared residual increases by 38-45% and hence the SD of prices offered increases by 6.2-6.7%. While low-LTV applications may be dealt with by more junior staff following set rules, or may even be delegated to a computer, the higher the LTV ratio and hence the higher the estimated credit risk the more often is the decision escalated to more senior staff, under whom our set of standard regressors need not always have the same marginal effects. Relatedly, we observe that the squared residual increases by 15-24%, and hence the residual by 3.9-4.9% whenever the proposed lending collateral is a less standardized object such as a villa, holiday home or multi-family house rather than more standard and hence easier-to-value apartments or single-family homes. This is consistent with the predictions in Petersen and Rajan (1995) whereby banks exert more discretion when lending to more "opaque" and hence harder-to-value firms. The findings support *Hypothesis 3a.*

Looking at bank characteristics, we find that each percent increase in the responding bank's total assets reduces the squared residual by between 8-20% and hence the residual by 2.8-4.5%, while each percentage point increase in a bank's share of total assets allocated to mortgages reduces the squared residual by 2-3% and hence the residual by 1.4-1.7%. Both findings confirm our *Hypothesis 3b*, whereby larger or more mortgage-specialized banks have more previous observations to allow them devising more reliable rules, and have stronger incentives to invest fine-tuning such rules.

Having thus analyzed the role of standard household and bank characteristics, we look next at the same measures of competition intensity and credit risk as analyzed above. Column 2 shows that applicants from cantons with higher HHI, or more other web competitors, receive not only more attractive but also more automated responses. Next, Column 4 shows that banks exercise again more discretion when house prices in the applicant's canton are deemed more over-heated relative to those in the bank's home canton. This is again in line with the discretion response to other risk-relevant characteristics discussed above. Finally, Column 6 finds that whenever a response is sent out in less than the median response time of 48 hours, squared residuals decrease by 17% and residuals therefore by 4.1%. This is likely precisely why they can be sent out faster. Finally and importantly, we find that with each additional month for which the bank has been offering mortgages through the platform, squared residuals decrease by about 3% and residuals therefore by 1.7%. Assuming as a simplified approximation that this marginal effect of each month of online experience is the same for all 69 months observed, this implies a decrease in discretion by more than 90% between the first and last sample month, supporting *Hypothesis 3c*.

5.4 Results on Disperson of Offers

In *Table 5*, Columns 1 and 2 use as outcome the SD of spreads within the set of responses received by each household, while Columns 3 and 4 use the same SD but for robustness rescale it by the mean spread offered to that household. Columns 1 and 3 control additionally for year*month fixed effects, while Columns 2 and 4 do not. As each household's set of responses consists by definition of responses from multiple different banks, we cannot analyse how the dispersion of offers is related to e.g. price correlation, relative over-heating or distance, but we can analyse firstly how it varies with our measures of competition intensity in the applicant's canton, and secondly with applicant-specific risk factors.

Starting with the coefficient on the HHI, we find first that the SD is on average about 24bp, or about 20% of the mean spread, lower in a (hypothetically) fully monopolized cantonal market. In a similar vein, we also find less dispersion the more other banks are also bidding online, although the size of this effect is below 1bp per additional competitor and therefore seems economically negligeable. By contrast, the effect of a more concentrated market does not, and suggests that most banks agree which cantons are most attractive to enter through the online channel.

By contrast, banks appear to agree less when the credit risk associated with a household is higher. In particular, we find that whenever the LTV ratio exceeds two-thirds, the SD of spreads is on average 4bps, or about 3% of the mean spread offered to that household, higher. In line with that, it tends to be lower for refinancing applications, which tend not only to have already reduced their LTV ratios but have also proven already for a number of years that they are able and willing to keep servicing their mortgage as agreeds with their previous financing partner(s). We take this to confirm our *Hypothesis 4*. It can be attributed firstly to inter-bank differences in the ability and willingness to take on riskier clients, and secondly to the fact that borrowers with higher LTV ratios may still be more attractive for banks from further away so that house prices in their existing portfolio exhibit on average a lower correlation with those in the applicant's canton, than for banks already concentrated in that canton.

5.5 Results when Accounting for Possible Selectiveness of Prices Offered

In *Table 17* we explore how robust our effects on pricing are to controlling for possible selectiveness of where we observe an offer and hence a price in the first place. Columns 1-2 include the same competition measures as in *Table 2* and Columns 3-4 include the same risk measures as in *Table 3*. Columns 5-6 include instead the fast response and bank web experience measures as in *Table 4*. Within these four pairs, the first column shows always the results of estimating the *selection equation*, which atop all other regressors includes the 2nd semester indicator. The second column in each pair shows the resulting main equation estimates. To start with, results on the *selection equation* show that responses sent out in the second half of the year are between 5% (Column 5) and 11% (Column 3) less likely to be offers, so the instrument is certainly sufficiently strong. The *exclusion restriction* whereby pricing depends on the bank's own refinancing costs, risks and competition intensity but not on the time of year can by definition not be tested formally, but month-dependent pricing after controlling for all other regressors seems unlikely. As discussed above, offer propensities vary significantly also with amongst others household characteristics, competition intensity, and risk characteristics, suggesting that the pricing on offers never sent could differ from that on offers that are sent out. To simplify, our Heckman estimates do not instrument HHI, so results of Column 2 are best compared with those in Column 4 of *Table 11*. There we find a coefficient on HHI of -0.48, while here we get only -0.29, although sign and statistical significance remain practically unchanged. Likewise, results of Column 4 are best compared to those in Column 4 of *Table 15*, where they are smaller than the Heckman ones. Overall, we conclude that possible selectiveness of responses does decrease coefficients on HHI and decrease those on price correlations, but in both cases sign and significance remain unchanged. Therefore we deem it appropriate to focus at the baseline on the pricing of offers actually sent out rather than the hypothetical pricing of offers never sent out.

6 Conclusion

In this paper we have investigated how mortgage lending changes through the provision of an online platform where potential borrowers from across the country can apply and potential lenders from across the country can respond. For banks this removes the usual constraint that most banks can interact with most borrowers only if they maintain a branch nearby that borrower's location. For us as researchers the platform, which has provided us with all borrower information as forwarded to the participating banks, allows to attribute a bank's propensity to offer and the attractiveness of its offers directly to properties of the applicant's region, and its relationship with the bank's own location and prior portfolio. In particular, the fact that we observe the responses from different, and differently located, banks, as well as responses from each bank to different, and differently located, households, allows us to close down any biases from the selection of different types of households to different types of banks. Doing so, we obtain findings along three key dimensions.

First, we observe that the more concentrated is a cantonal mortgage market prior to the operation of the web platform analyzed, the more often do banks respond with an offer and the more attractive is the price they offer. We interpret this as banks seizing the online platform to get "a foot in the door" in those markets. For potential borrowers located in hitherto more concentrated markets, this implies that the availability of an online platform can lead to more and better mortgage offers.

Second, in line with banks' general strife to use the online channel to enter profitable markets, we see that the average bank makes particularly often and particularly attractive offers when bidding for clients clients in regions where house prices are less correlated with those in their home canton, as well as cantons where house prices are deemed less over-heated relative to those in the bank's home canton. Hence the online platform allows banks to improve the inter-regional allocation of their mortgage portfolio and hence ceteris paribus improve their risk management in line with arguments in amongst others Quigly 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 validly raised by Loutskina and Strahan (2014), in the market analyzed. For collateral values here are assessed with the same hedonic models country-wide and information on borrowers are equally reliable regardless of the region. Yet we acknowledge that we cannot explicitly compare default rates on more versus less distant residential mortgage lending, as the period analyzed has few defaults.

Third, we investigate explicitly the dispersion of offered prices around those predicted by the set of factors discussed above, and interpret it as cases in which decision-making is not 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. More interestingly, we also find that the degree of automation thus measured increases the longer the bank has been offering mortgages to individual customers through the online platform, suggesting that longer participation can help banks to reduce operational costs. Importantly, 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. We do however observe banks to price in all commonly considered mortgage risk factors such as LTV and LTI ratios, as well as estimates of regional house price over-heating, so we have no reason to suspect that banks are less careful when offering mortgages online than when they do so offline.

Overall our findings suggest potential improvements for borrowers as well as for financial stability that can be achieved through online platforms, so it will be interesting to see how the use of platforms with associated costs and risks develops going forward.

In the present paper we have been able to analyze this in an unusually clear way by isolating banks' willingness to lend to different regions from their pre-existing branch networks, and by exploiting quasi-experimental variation both in our HHI measure of prior market concentration and in the degree to which each mortgage may be deemed to complement a bank's pre-existing mortgage portfolio for risk management purposes.

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Tables

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	25'125	566'274	332'695	100'000	2'000'000
Refinancing (0/1)	25'125	0.46	0.50	0	1
Loan-to-Value (LTV)	25'125	64.50	17.30	15.00	90.00
I (LTV > 67%)	25'125	0.53	0.50	0	1
I (LTV > 80%)	25'125	0.08	0.26	0	1
Loan-to-Income (LTI)	25'125	3.59	1.52	0.69	9.62
I (LTI > 4.5)	25'125	0.23	0.42	0	1
I (LTI > 5.5)	25'125	0.08	0.27	0	1
HH Income	25'125	167'603	88'961	48'000	600'000
Rental Income	25'125	4'232	16'880	0	116'000
Other Income	25'125	9'381	28'329	0	200'000
Wealth incl. Pension Fund	25'125	469'333	515'877	10'000	3'180'000
Age	25'125	46	10	28	73
(B) Regional Characteristics					
Herfindahl-Hirschmann Index (HHI) for Growth	25'125	0.18	0.05	0.09	0.57
Herfindahl-Hirschmann Index (HHI) for Levels	25'125	0.19	0.05	0.12	0.49
Number of Online Providers (NOP)	25'125	10.92	2.52	4	14
Multi-Market Contact (MMC)	25'125	0.07	0.03	0.05	0.40
Single-Family Home Price Growth	25'125	4.07	4.07	-3.99	15.27
Big Banks' Prior Mortgage Market Share	25'125	0.31	0.08	0.09	0.57
Big Banks' Prior Branch Share	25'125	0.18	0.08	0.06	0.33
(C) Bank Characteristics					
Bank Total Assets (TA)	25'125	16'932	12'841	434	37'804
Mortgages/TA	25'125	69.82	10.43	39.79	90.62
Deposits/TA	25'125	47.80	17.90	16.72	65.63
Capital Ratio	25'125	7.25	1.03	4.72	11.33
Bank Web Experience in Months	25'125	34.39	14.35	0.00	69.00
(D) Interaction Characteristics					
House price growth correlation	25'125	0.77	0.19	0.15	1.00
Relative Over-Heating (ROH)	25'125	1.16	0.17	0.75	2.08
Language Mismatch	25'125	0.22	0.41	0	1
Distance Applicant Bank HQ (100km)	25'125	1.10	0.87	0.00	4.22
Driving Time Applicant Bank HQ (hours)	25'125	1.30	0.91	0.00	4.42
Responses per Application	25'125	4.24	1.45	1.00	10.00
Response Time in Hours	25'125	97.41	151.72	-2.73	789.10
I (Response in <= 48 hours)	25'125	0.53	0.50	0	1
I (Offer = 1)	25'125	0.82	0.38	0	1
Weighted Offered Fixation Period	20'583	7.36	2.93	0.25	10.00
Weighted Rate Offered	20'583	2.16	0.56	0.93	3.25
Weighted Spread Offered	20'583	0.90	0.21	0.49	1.52

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. (B) shows bank-relevant characteristics of the region where the collateral is based. The NOP, HHI and MMC measures of competition vary across the 26 cantons. (C) shows key bank characteristics, as well as the number of months for which the bank has been bidding online, and the fraction of responses sent out in <= 48 hrs. (D) shows key response characteristics. The distance between applicant and bank headquarters is measured once in 100km and once in hours. House price correlation measures the correlation between year-on-year growth rates in the applicant's and the bank's canton. Relativer over-heating scales the percentage to which house prices in the applicant's canton are deemed overheated by FPRE by the percentage in the bank's home 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 prevailing on that day.

Table 2: Competition

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
HHI	3.15***	-1.63***	1.80*	-1.89***	4.00***	-1.38***
	(0.98)	(0.20)	(1.00)	(0.71)	(0.92)	(0.44)
No. of Web Lenders	0.02***	-0.00	0.02***	-0.00	0.02***	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SFH Price Growth	-2.51***	0.54***	-1.80**	0.82	-1.89**	0.17
	(0.90)	(0.18)	(0.90)	(0.61)	(0.76)	(0.31)
I(LTV>=67%)	-0.06***	0.05***	-0.05**	0.05**	-0.05**	0.05**
	(0.02)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)
I(LTV>=80%)	-0.84***	0.03***	-0.85***	0.03***	-0.85***	0.03***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=4.5)	-0.19***	0.01***	-0.18***	0.01	-0.18***	0.01
	(0.03)	(0.00)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=5.5)	-0.80***	0.03***	-0.85***	0.02**	-0.84***	0.02***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
I(Refinancing)	-0.08***	-0.02***	-0.10***	-0.02***	-0.10***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)
Ln(Total Assets)			0.05***	-0.04***		
			(0.02)	(0.01)		
Mortgages/TA			0.02***	-0.00**		
			(0.00)	(0.00)		
Deposits/TA			-0.02***	0.00		
			(0.00)	(0.00)		
Equity/TA			0.04***	0.02*		
			(0.01)	(0.01)		
Constant	0.50***	1.30***	-0.41	1.77***	0.36	1.33***
	(0.17)	(0.03)	(0.27)	(0.19)	(0.33)	(0.07)
Observations	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.16		0.17		0.26
Estimation	IV Probit	2SLS	IV Probit	2SLS	IV Probit	2SLS
Bank FE	No	No	No	No	Yes	Yes

Prior competition in the applicant's canton is measured by the Herfindahl-Hirschmann Index (HHI), the sum of squared market shares in the first difference of cantonal mortgage volumes, in 2010. This HHI is instrumented with 2009 market shares of the two big banks UBS and CS who had to significantly cut down new lending after losses in the US market and subsequent deposit withdrawals (Brown et al, 2019). Columns with unequal numbers show marginal effects from (IV) Probit regressions. Controls include the number of other web lenders active in that canton and the year-on-year growth of quality-adjusted single-family home (SFH) prices and indicators for the applicant's loan-to-value (LTV) and loan-to-income (LTI) ratio. 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.

Table 3: Risk Management

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
Price Corr	-4.48***	1.03***	-3.64***	0.58***	-3.71***	0.48***
	(0.55)	(0.17)	(0.44)	(0.08)	(0.49)	(0.11)
Rel. Over-Heat.			-0.60***	0.22***	-0.08	0.17***
			(0.12)	(0.02)	(0.12)	(0.02)
HHI					-8.23***	0.19
					(2.03)	(0.41)
# (web lenders)					0.06***	-0.01***
					(0.01)	(0.00)
I(LTV>=67%)	-0.06***	0.06***	-0.06***	0.06***	-0.07***	0.06***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
I(LTV>=80%)	-0.63***	0.01	-0.71***	0.02**	-0.64***	0.02**
	(0.06)	(0.01)	(0.04)	(0.01)	(0.08)	(0.01)
I(LTI>=4.5)	-0.12***	-0.01*	-0.13***	-0.01	-0.10***	-0.00
	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
I(LTI>=5.5)	-0.72***	0.03***	-0.78***	0.03***	-0.73***	0.03***
	(0.05)	(0.01)	(0.04)	(0.01)	(0.06)	(0.01)
I(Refinancing)	-0.08***	-0.02***	-0.09***	-0.02***	-0.11***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Ln(Total Assets)	-0.27***	0.02*	-0.20***	-0.01	-0.12***	-0.02***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.03)	(0.00)
Mortgages/TA	-0.00	0.00	-0.00	-0.00	0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Deposits/TA	0.02***	-0.01***	0.02***	-0.00***	0.01**	-0.00***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.33***	-0.05***	0.28***	-0.03***	0.29***	-0.02**
	(0.04)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)
Constant	3.69***	0.69***	3.84***	0.77***	2.95***	1.04***
	(0.53)	(0.15)	(0.57)	(0.10)	(0.57)	(0.11)
Obs.	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.19		0.18		0.21

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.

Table 4: Rules vs. Discretion in Online Mortgage Pricing

	(1) Price	(2) Discretion	(3) Price	(4) Discretion	(5) Price	(6) Discretion
I(LTV>=67%)	0.04***	0.45***	0.04***	0.44***	0.04***	0.38***
	(0.00)	(0.07)	(0.00)	(0.07)	(0.00)	(0.07)
I(LTV>=80%)	0.02***	0.04	0.02***	0.05	0.02***	0.06
	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.08)
I(LTI>=4.5)	0.00	0.05	0.00	0.04	0.00	0.00
	(0.00)	(0.10)	(0.00)	(0.09)	(0.00)	(0.09)
I(LTI>=5.5)	0.02***	0.00	0.03***	-0.04	0.03***	-0.03
	(0.01)	(0.14)	(0.01)	(0.13)	(0.01)	(0.13)
I(Refinancing)	-0.02***	-0.05	-0.02***	-0.05	-0.02***	-0.05
	(0.00)	(0.07)	(0.00)	(0.06)	(0.00)	(0.06)
I (SFH)	-0.01***	-0.08	-0.01*	0.00	-0.01*	-0.07
	(0.00)	(0.07)	(0.00)	(0.07)	(0.00)	(0.06)
I (Nonstandard)	0.01**	0.15*	0.02***	0.24***	0.02***	0.17**
	(0.00)	(0.08)	(0.00)	(0.07)	(0.00)	(0.07)
Ln(Total Assets)	-0.04***	-0.19***	-0.04***	-0.18***	-0.07***	-0.09**
	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)	(0.04)
Mortgages/TA	-0.00***	-0.03***	-0.00***	-0.02***	-0.00***	-0.03***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Deposits/TA	0.00	0.02***	-0.00	0.01	0.00***	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.02***	0.07**	0.01***	0.02	0.01***	0.09***
	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)	(0.03)
Growth HHI	-0.28***	-1.43**				
	(0.03)	(0.62)				
NOP	-0.00***	-0.05***				
	(0.00)	(0.01)				
Price Correlation			0.03***	0.17		
			(0.01)	(0.20)		
Relative Over-heating			0.10***	2.09***		
			(0.01)	(0.28)		
I(Fast Response)					-0.01***	-0.17***
					(0.00)	(0.05)
Bank Web Experience					0.01***	-0.03***
					(0.00)	(0.01)
Constant	1.51***	-0.67	1.06***	-4.01	1.19***	-0.31
	(0.04)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
R2	0.277		0.272		0.268	
Year*Month FE	Yes	Yes	Yes	Yes	No	No

Discretion is the variance unexplained in the pricing regressions. Columns 2, 4, 6 and 8 show that it is not orthogonal to key characteristics but varies with them. Bank's Web Experience is the number of months for which the bank has been offering mortgages through the platform. All other regressors as in Tables 1 and 2 above. Standard errors clustered by bank * household zip in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table 5: Offer Dispersion within each Household

	(1) SD	(2) SD	(3) SD/Mean	(4) SD/Mean
HHI	-24.18***	-24.15***	-10.82	-11.76
	(3.24)	(3.25)	(14.62)	(14.69)
# (web lenders)	-0.15**	-0.17**	-0.05	-0.06
	(0.07)	(0.07)	(0.16)	(0.16)
I(LTV>=67%)	4.27***	4.30***	2.81**	2.84**
	(0.41)	(0.42)	(1.36)	(1.38)
I(LTV>=80%)	0.91	1.31	-0.39	0.35
	(0.82)	(0.83)	(1.19)	(1.11)
I(LTI>=4.5)	0.05	-0.02	0.22	0.11
	(0.43)	(0.44)	(1.68)	(1.70)
I(LTI>=5.5)	-0.77	-0.69	-2.12	-2.32
	(0.73)	(0.72)	(1.78)	(1.64)
I(Refinancing)	-0.41	-0.30	-3.06**	-2.41*
	(0.39)	(0.39)	(1.53)	(1.31)
Constant	17.40***	19.07***	15.06***	19.88***
	(1.87)	(1.11)	(3.57)	(3.57)
Obs.	5'563	5'563	5'563	5'563
R2	0.07	0.04	0.02	0.00
Year*Month FE	Yes	No	Yes	No

Here we compute the standard deviation (SD) of spreads (amount-weighted where an offer consists of 2 or 3 rather than only 1 tranche) between offered rates and maturity-congruent interest swap rates applicable on the same day across all 1-10 offers an application receives. SD are measured in basis points rather than percentage points to facilitate interpretation. Then Columns 1 and 2 regress that SD on all regressors fixed within an application, while 3 and 4 do so for the SD rescaled by the mean spread a household is offered. Columns 1 and 3 control additionally for year*month fixed effects to proxy amongst others for the prevailing interest rate environment, while Columns 2 and 4 do not. Standard errors clustered by household zip in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Online Appendix for:

The Geography of Mortgage Lending in Times of FinTech

Table 6: Geographical Representativeness of Households

	(1)	(2)	(3)	(4)
Canton	**Number of Applications**	**Percentage of Applications**	**% of Mortgages Swiss Household Panel**	**% of Volume All Swiss Banks**
Aargau	850	12.28	11.70	8.73
Appenzell AR	4	0.06	1.12	0.62
Appenzell IR	33	0.48	0.56	0.18
Basel Land	287	4.15	3.64	3.86
Basel Stadt	106	1.53	0.28	1.92
Berne	982	14.19	17.65	10.77
Fribourg	220	3.18	5.88	3.23
Geneva	162	2.34	2.24	5.06
Glarus	30	0.43	0.84	0.44
Graubünden	163	2.36	1.96	3.33
Jura	26	0.38	0.56	0.75
Lucerne	256	3.70	5.32	4.64
Neuchatel	73	1.05	5.04	1.53
Nidwalden	20	0.29	0.84	0.54
Obwalden	35	0.51	0.84	0.47
Schaffhausen	71	1.03	0.28	0.94
Schwyz	142	2.05	1.96	2.37
Solothurn	238	3.44	2.80	3.37
St.Gallen	339	4.90	6.16	5.73
Thurgau	233	3.37	3.08	3.48
Ticino	182	2.63	3.64	4.73
Uri	17	0.25	0.00	0.40
Valais	223	3.22	3.92	3.59
Vaud	607	8.77	7.28	8.07
Zug	118	1.71	0.56	2.04
Zurich	1'503	21.72	14.29	19.19
Total	6'920	100.00	100.00	100.00

The distribution in our sample counts each of the 6’920 mortgage applications submitted via Comparis.ch once. We can compare it first with the percentages of households in the nationally representative Swiss Household Panel (SHP), provided by the Federal Office of Statistics, who transition to home ownership in 2008-13 and therefore have outstanding mortgage debt in 2014. Finally, we also compare the distribution with that of outstanding mortgage debt already on banks’ balance sheets as reported to the supervisory authority in 2013. Note that the latter is available only based on all mortgages currently on banks’ balance sheets, rather than on new lending only. Based on either comparison, we conclude that the geographical coverage of our mortgage applications is largely representative and is not, for instance, biased towards more urban areas.

Table 7: Geographical Representativeness of Banks

	Comparis		B&M (2018)	
Canton	**# banks**	**% of banks**	**# banks**	**% of banks**
Aargau	2	7.41	3	6.00
Appenzell AR	0	0.00	0	0.00
Appenzell IR	0	0.00	1	2.00
Basel Land	0	0.00	1	2.00
Basel Stadt	2	7.41	4	8.00
Berne	4	14.81	9	18.00
Fribourg	0	0.00	1	2.00
Geneva	1	3.70	1	2.00
Glarus	1	3.70	1	2.00
Graubünden	0	0.00	1	2.00
Jura	0	0.00	1	2.00
Lucerne	1	3.70	1	2.00
Neuchatel	0	0.00	1	2.00
Nidwalden	0	0.00	1	2.00
Obwalden	1	3.70	1	2.00
Schaffhausen	0	0.00	1	2.00
Schwyz	1	3.70	1	2.00
Solothurn	2	7.41	4	8.00
St. Gallen	4	14.81	3	6.00
Thurgau	0	0.00	1	2.00
Ticino	1	3.70	1	2.00
Uri	1	3.70	1	2.00
Valais	1	3.70	1	2.00
Vaud	1	3.70	4	8.00
Zug	0	0.00	1	2.00
Zurich	4	14.81	5	10.00
Total	27	100.00	50	100.00

This table compares the distribution of banks' headquarters across the 26 cantons of Switzerland with that in Basten and Mariathasan (2018), who select the universe of Swiss retail banks based on the FINMA definition that at least 55% of bank income must be net interest income or loan fees, as opposed to stem from own trading or wealth management advisory services.

Table 8: Non-Geographical Representativeness of Households and Banks

A. Comparison of household characteristics with the Swiss Household Panel (SHP)

	Our sample	SHP	Difference
	(1)	(2)	(3)
Age	46.10	45.51	0.60
	(10.21)	(1.17)	(10.45)
Household Income	167'603	147'649	19'999
	(89'061)	(318'066)	(172'429)
Number of observations	25'125	357	25'494

B. Comparison of mortgage risk characteristics with SNB (2014)

	Our sample	SNB	Difference
	(1)	(2)	(3)
Loan-to-Value (LTV) ratio > 80% (0/1)	0.07	0.16	-0.09
	(0.26)	(--)	(--)
Payment-to-Income (PTI) ratio>33% (0/1)	0.39	0.40	-0.01
	(0.13)	(--)	(--)
Number of observations	25'125	(--)	(--)

C. Comparison of bank characteristics with Basten and Mariathasan (2018)

	Our sample	B&M (2018)	Difference
	(1)	(2)	(3)
Total Assets	9'866	12'185	-2'319
	(11'910)	(22'215)	(25'206)
CET1 in % of Total Assets	7.19	7.75	-0.56
	(1.53)	(1.66)	(2.26)
Deposits in % of Total Assets	67.53	47.71	19.83
	(5.47)	(11.00)	(12.28)
Number of observations	27	50	77

Panel A compares households in our sample with those in the Swiss Household Panel (SHP) who recently bought a house or apartment. Panel B compares the 2 key risk characteristics of each mortgage with those reported in the SNB Financial Stability Report 2014, and Panel C compares banks in our sample with the full sample of those 50 Swiss banks focused on deposit-taking and lending. We always compare all characteristics available both in our sample and in the respective benchmark. Column (1) always shows the mean value in our sample and in brackets the standard error. Column (2) shows the respective values for the benchmark sample, except for Panel B where none are given. Column (3) computes the difference and the pooled standard error to evaluate its statistical significance.

Table 9: First Stage Regressions for Competition Analyses

	(1)	(2)	(3)
	HHI	HHI	HHI
Prior big bank market share	-0.13***	-0.13***	-0.14***
	(0.01)	(0.01)	(0.01)
# (web lenders)	0.00	0.00***	0.00
	(0.00)	(0.00)	(0.00)
SFH Price Growth	0.74***	0.73***	0.56***
	(0.04)	(0.04)	(0.04)
I(LTV>=67%)	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
I(LTV>=80%)	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
I(LTI>=4.5)	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
I(LTI>=5.5)	-0.00***	-0.00***	-0.00**
	(0.00)	(0.00)	(0.00)
I(Refinancing)	-0.00***	-0.00***	-0.00**
	(0.00)	(0.00)	(0.00)
Ln(Total Assets)		0.01***	
		(0.00)	
Mortgages/TA		0.00***	
		(0.00)	
Deposits/TA		-0.00***	
		(0.00)	
Equity/TA		0.00	
		(0.00)	
Constant	0.15***	0.09***	0.18***
	(0.01)	(0.01)	(0.01)
Observations	25'125	25'125	25'125
R2	0.11	0.12	0.20
F statistic	216.1	210.1	207.7
Estimation	OLS	OLS	OLS
Bank FE	No	No	Yes

This table shows the first-stage regressions behind our baseline IV regressions in Table 2. Here the Herfindahl-Hirschmann Index (HHI) of the cantonal concentration of new lending in the first year of our dataset is regressed on the shares in existing levels of lending held by UBS plus Credit Suisse in the year before. All control variables are identical to those used in Table 2. In particular, Column 1 controls for canton and household characteristics only, Column 2 adds bank characteristics, and Column 3 replaces bank characteristics with bank fixed effects. Standard errors clustered by bank * household zip in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table 10: Competition, Instrumenting HHI with Big Banks' Branch Share

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
HHI	1.86	-1.16***	0.58	-0.85*	0.48	-1.17**
	(1.76)	(0.29)	(1.79)	(0.48)	(1.97)	(0.52)
# (web lenders)	0.02***	-0.00	0.02***	-0.00**	0.02***	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SFH Price Growth	-1.65	0.21	-1.00	0.12	-0.20	0.07
	(1.28)	(0.23)	(1.27)	(0.45)	(1.10)	(0.31)
I(LTV>=67%)	-0.06***	0.05***	-0.05**	0.05**	-0.05**	0.05**
	(0.02)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)
I(LTV>=80%)	-0.85***	0.03***	-0.85***	0.03***	-0.86***	0.03***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=4.5)	-0.19***	0.01**	-0.18***	0.00	-0.17***	0.01
	(0.03)	(0.00)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=5.5)	-0.81***	0.03***	-0.85***	0.03***	-0.86***	0.03***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
I(Refinancing)	-0.09***	-0.02***	-0.10***	-0.02***	-0.10***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)
Ln(Total Assets)			0.06***	-0.05***		
			(0.02)	(0.01)		
Mortgages/TA			0.02***	-0.00**		
			(0.00)	(0.00)		
Deposits/TA			-0.02***	0.00		
			(0.00)	(0.00)		
Equity/TA			0.04***	0.01**		
			(0.01)	(0.01)		
Constant	0.65***	1.24***	-0.35	1.71***	0.92**	1.30***
	(0.25)	(0.04)	(0.29)	(0.17)	(0.43)	(0.10)
Observations	25,125	20,583	25,125	20,583	25,113	20,583
R2		0.20		0.27		0.28
Estimation	IV Probit	2SLS	IV Probit	2SLS	IV Probit	2SLS
Bank FE	No	No	No	No	Yes	Yes

Columns with unequal numbers show marginal effects from (IV) Probit regressions. While Table 2 instrumented the Herfindahl-Hirschmann Index (HHI) of the prior concentration of total (online plus offline) mortgage lending with the prior market share of the two big banks in cantonal mortgage volumes, here we instrument it with their prior share in cantonal bank branches as reported in Brown et al (2019). The number of competitors also bidding for applications in the canton ranges from 4 to 14. Single-family home (SFH) price growth in the applicant's canton is lagged by one year. 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 further applicant characteristics (income, wealth, debt, age, house type) are omitted but do not change results when included in addition. 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.

Table 11: Competition, with HHI not Instrumented

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
HHI	0.62***	-0.42***	0.35*	-0.38***	0.42*	-0.37***
	(0.22)	(0.04)	(0.21)	(0.03)	(0.22)	(0.03)
# (web lenders)	0.02***	-0.00**	0.02***	-0.00***	0.02***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SFH Price Growth	-0.81	-0.31***	-0.85	-0.20**	-0.17	-0.34***
	(0.61)	(0.10)	(0.61)	(0.09)	(0.61)	(0.09)
I(LTV>=67%)	-0.06***	0.05***	-0.05**	0.05***	-0.05**	0.05***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
I(LTV>=80%)	-0.85***	0.03***	-0.85***	0.03***	-0.86***	0.03***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=4.5)	-0.18***	0.01*	-0.18***	-0.00	-0.17***	0.00
	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
I(LTI>=5.5)	-0.81***	0.04***	-0.86***	0.03***	-0.86***	0.03***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
I(Refinancing)	-0.09***	-0.02***	-0.10***	-0.02***	-0.10***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Ln(Total Assets)			0.06***	-0.05***		
			(0.02)	(0.00)		
Mortgages/TA			0.02***	-0.00***		
			(0.00)	(0.00)		
Deposits/TA			-0.02***	0.00***		
			(0.00)	(0.00)		
Equity/TA			0.04***	0.01***		
			(0.01)	(0.00)		
Constant	0.79***	1.16***	-0.34	1.68***	0.93***	1.17***
	(0.13)	(0.02)	(0.27)	(0.04)	(0.30)	(0.02)
Observations	25,125	20,583	25,125	20,583	25,113	20,583
R2		0.23		0.28		0.31
Estimation	Probit	OLS	Probit	OLS	Probit	OLS
Bank FE	No	No	No	No	Yes	Yes

Columns with unequal numbers show marginal effects from (IV) Probit regressions. While Tables 2 and A4 instrument the Herfindahl-Hirschmann Index (HHI) of the prior concentration of total (online plus offline) mortgage lending with big banks' prior share In cantonal mortgage lending and cantonal branches respectively, this table does for comparison regress banks' online offer behavior directly on HHI and controls. The number of competitors also bidding for applications in the canton ranges from 4 to 14. Single-family home (SFH) price growth in the applicant's canton is lagged by one year. 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.

Table 12: Competition, with Non-Instrumented Level-Based HHI, and MMC

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
Level-based HHI	0.89***	-0.43***	0.58**	-0.34***	0.65**	-0.44***
	(0.28)	(0.05)	(0.28)	(0.04)	(0.29)	(0.04)
# (web lenders)	1.04**	-0.48***	0.74	-0.62***	1.78***	-0.40***
	(0.48)	(0.08)	(0.47)	(0.08)	(0.52)	(0.08)
Multi-Market Contact	0.03***	-0.01***	0.03***	-0.01***	0.03***	-0.01***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
SFH Price Growth	-1.19*	-0.19*	-1.12*	-0.17*	-0.30	-0.20**
	(0.66)	(0.10)	(0.65)	(0.09)	(0.66)	(0.09)
I(LTV>=67%)	-0.06***	0.05***	-0.05**	0.05***	-0.05**	0.05***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
I(LTV>=80%)	-0.85***	0.03***	-0.85***	0.03***	-0.86***	0.03***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=4.5)	-0.19***	0.01**	-0.18***	0.00	-0.18***	0.00
	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
I(LTI>=5.5)	-0.81***	0.04***	-0.86***	0.03***	-0.86***	0.03***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
I(Refinancing)	-0.09***	-0.02***	-0.10***	-0.02***	-0.10***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Ln(Total Assets)			0.06***	-0.05***		
			(0.02)	(0.00)		
Mortgages/TA			0.02***	-0.00***		
			(0.00)	(0.00)		
Deposits/TA			-0.02***	0.00***		
			(0.00)	(0.00)		
Equity/TA			0.04***	0.02***		
			(0.01)	(0.00)		
Constant	0.57***	1.25***	-0.46*	1.77***	0.56*	1.27***
	(0.14)	(0.02)	(0.28)	(0.04)	(0.31)	(0.02)
Observations	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.232		0.281		0.311
Estimation	Probit	OLS	Probit	OLS	Probit	OLS
Bank FE	No	No	No	No	Yes	Yes

Columns with unequal numbers show marginal effects from (IV) Probit regressions. While the Herfindahl-Hirschmann Index (HHI) in Tables 2, A4 and A5 is computed as the sum of squared shares in cantonal mortgage growth, here we compute it based on cantonal mortgage levels. Like in Table A5 we do not instrument it. We additionally control for the extent to which banks lending to the applicant's canton have Multi-Market Contact (MMC). The number of competitors also bidding for applications in the canton ranges from 4 to 14. Single-family home (SFH) price growth in the applicant's canton is lagged by one year. 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 further applicant characteristics (income, wealth, debt, age, house type) are omitted but do not change results when included in addition. 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.

Table 13: First Stage Regressions for Table 3 on Risk Management

	(1) Price Corr	(2) Price Corr	(3) Price Corr	(4) HHI
I(Lang. Mismatch)	-0.10***	-0.15***	-0.19***	0.03***
	(0.01)	(0.02)	(0.02)	(0.00)
Prior UBS&CS share			0.43***	-0.16***
			(0.02)	(0.01)
Rel. Over-Heating		-0.22***	-0.33***	0.10***
		(0.02)	(0.02)	(0.01)
# (web lenders)			0.01***	0.00***
			(0.00)	(0.00)
I(LTV>=67%)	-0.00	-0.00**	-0.00	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
I(LTV>=80%)	0.01***	0.01***	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
I(LTI>=4.5)	0.01**	0.01***	0.01**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
I(LTI>=5.5)	-0.01	-0.00	0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
I(Refinancing)	-0.00	-0.00	-0.00**	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Ln(Total Assets)	-0.07***	-0.08***	-0.07***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Mortgages/TA	-0.00***	-0.01***	-0.01***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Deposits/TA	0.01***	0.01***	0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.06***	0.05***	0.05***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.13***	1.59***	1.55***	-0.10***
	(0.06)	(0.08)	(0.08)	(0.02)
Obs.	25'125	25'125	25'125	25'125
R2	0.51	0.52	0.58	0.10
F statistic	46.82	75.16	116.4	43.32

Column 1 shows the first stage regression underlying Columns 1-2 of Table 3 and Column 2 shows those underlying Columns 3-4 of Table 3. Finally, Columns 3 and 4 show both first stage regressions underlying Columns 5-6 of Table 3. All other regressors as in Tables 2 and 3 above. 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.

Table 14: Risk Management, instrumenting Price Corr also with Distance

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
Price Corr	-0.01	0.17***	-0.13	0.22***	0.20	0.22***
	(0.20)	(0.03)	(0.21)	(0.03)	(0.38)	(0.04)
Rel. Over-Heating			-0.05	0.17***	-0.17	0.18***
			(0.10)	(0.02)	(0.11)	(0.02)
HHI					4.38**	-0.69***
					(1.99)	(0.21)
# (web lenders)					0.01	-0.01***
					(0.01)	(0.00)
I(LTV>=67%)	-0.05**	0.05***	-0.05**	0.06***	-0.04*	0.06***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
I(LTV>=80%)	-0.85***	0.02***	-0.84***	0.02***	-0.84***	0.02***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)
I(LTI>=4.5)	-0.17***	-0.00	-0.17***	-0.00	-0.19***	0.00
	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
I(LTI>=5.5)	-0.86***	0.03***	-0.86***	0.03***	-0.82***	0.03***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)
I(Refinancing)	-0.09***	-0.02***	-0.09***	-0.02***	-0.08***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Ln(Total Assets)	0.05**	-0.04***	0.04**	-0.03***	0.04**	-0.03***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Mortgages/TA	0.02***	-0.00***	0.01***	-0.00***	0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Deposits/TA	-0.02***	0.00	-0.01***	-0.00***	-0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.04**	0.00	0.05**	-0.00	0.02	-0.00
	(0.02)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)
Constant	-0.07	1.43***	0.10	1.15***	-0.56	1.28***
	(0.31)	(0.04)	(0.38)	(0.05)	(0.47)	(0.06)
Obs.	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.26		0.26		0.27

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 as well as with the distance in 100km (computed using HERE maps and the –georoute- command by Weber and Péclat, 2016). 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.

Table 15: Risk Management, without Instrumentation

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
Price Corr	-0.25***	0.05***	-0.26***	0.06***	-0.32***	0.05***
	(0.08)	(0.01)	(0.08)	(0.01)	(0.08)	(0.01)
Rel. Over-Heating			-0.07	0.14***	-0.03	0.15***
			(0.09)	(0.02)	(0.09)	(0.02)
HHI					0.16	-0.42***
					(0.21)	(0.03)
# (web lenders)					0.02***	-0.00***
					(0.00)	(0.00)
I(LTV>=67%)	-0.05**	0.05***	-0.05**	0.06***	-0.05**	0.06***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
I(LTV>=80%)	-0.84***	0.02***	-0.84***	0.02***	-0.85***	0.03***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
I(LTI>=4.5)	-0.17***	-0.00	-0.17***	-0.00	-0.18***	-0.00
	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
I(LTI>=5.5)	-0.86***	0.03***	-0.86***	0.03***	-0.86***	0.03***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
I(Refinancing)	-0.09***	-0.02***	-0.09***	-0.02***	-0.10***	-0.02***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Ln(Total Assets)	0.04**	-0.05***	0.03*	-0.04***	0.04**	-0.04***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Mortgages/TA	0.01***	-0.00***	0.01***	-0.00***	0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Deposits/TA	-0.01***	0.00***	-0.01***	0.00	-0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.06***	0.01***	0.06***	0.01***	0.06***	0.01***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Constant	0.13	1.53***	0.24	1.32***	-0.13	1.42***
	(0.27)	(0.04)	(0.32)	(0.04)	(0.33)	(0.04)
Obs.	25'125	20'583	25'125	20'583	25'125	20'583
R2		0.27		0.27		0.28

Columns with unequal numbers show marginal effects from Probit regressions. Here neither the price correlation nor the HHI measure are instrumented. 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. 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.

Table 16: Bank-Specific Rules vs. Discretion

	(1) Price	(2) Discretion	(3) Price	(4) Discretion	(5) Price	(6) Discretion
I(LTV>=67%)	-0.01	0.42***	-0.01	0.38***	-0.00	0.39***
	(0.03)	(0.08)	(0.03)	(0.07)	(0.03)	(0.07)
I(LTV>=80%)	0.06*	-0.04	0.07*	-0.01	0.06	-0.01
	(0.03)	(0.09)	(0.03)	(0.09)	(0.04)	(0.09)
I(LTI>=4.5)	0.09**	0.07	0.09**	0.05	0.07*	0.05
	(0.04)	(0.10)	(0.04)	(0.10)	(0.04)	(0.11)
I(LTI>=5.5)	-0.12	-0.05	-0.11	-0.06	-0.10	-0.04
	(0.08)	(0.15)	(0.09)	(0.14)	(0.09)	(0.14)
I(Refinancing)	-0.00	0.01	-0.00	0.01	-0.00	-0.02
	(0.03)	(0.07)	(0.03)	(0.06)	(0.03)	(0.06)
I (SFH)	0.07**	-0.06	0.06**	0.02	0.06**	-0.07
	(0.03)	(0.07)	(0.03)	(0.07)	(0.03)	(0.07)
I (Nonstandard)	0.09***	0.16**	0.08***	0.26***	0.08***	0.19**
	(0.02)	(0.08)	(0.02)	(0.08)	(0.02)	(0.08)
Ln(Total Assets)		-0.17***		-0.20***		-0.21***
		(0.04)		(0.04)		(0.05)
Mortgages/TA		-0.03***		-0.02***		-0.03***
		(0.01)		(0.01)		(0.01)
Deposits/TA		0.02***		0.01		0.03***
		(0.00)		(0.01)		(0.01)
Equity/TA		0.01		0.01		0.01
		(0.04)		(0.04)		(0.04)
Growth HHI	0.64	-0.80				
	(3.95)	(0.62)				
NOP	0.02	-0.04**				
	(0.11)	(0.01)				
Price Correlation			-0.09	-0.51**		
			(0.35)	(0.21)		
Relative Over-heating			-0.17	2.58***		
			(0.21)	(0.29)		
I(Fast Response)					-0.01	-0.16***
					(0.04)	(0.06)
Bank Web Experience					0.01***	0.01**
					(0.00)	(0.01)
Constant	0.50	-0.75	1.02*	-4.84	0.62***	-1.66
	(2.11)	(0.00)	(0.54)	(0.00)	(0.05)	(0.00)
R2	0.36		0.36		0.33	
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes

In contrast to the baseline discretion analyses in Table 4, here Columns 1, 3, 5 and 7 interact all regressors of interest with dummies for all except one bank, and additionally control main bank fixed effects instead of bank characteristics. Given space constraints we display only the effects for the baseline bank. Columns 2, 4, 6 and 8 do not interact with every single bank. Discretion is the variance unexplained in the pricing regressions. Bank's Web Experience is the number of months for which the bank has been offering mortgages through the platform. All other regressors as in Tables 1 and 2 above. Standard errors clustered by bank * household zip in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.

Table 17: Heckman

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
HHI	0.15	-0.29***				
	(0.21)	(0.04)				
# (web lenders)	0.01***	-0.00***				
	(0.00)	(0.00)				
SFH Price Growth	0.73**	-1.22***				
	(0.34)	(0.06)				
Price Corr.			-0.18**	0.14***		
			(0.08)	(0.01)		
Rel. Over-Heat.			-0.17**	0.40***		
			(0.08)	(0.01)		
I(Fast Response)					0.02	-0.01*
					(0.02)	(0.00)
Web Experience					-0.00***	0.01***
					(0.00)	(0.00)
I(LTV>=67%)	-0.01	0.05***	-0.02	0.06***	-0.00	0.05***
	(0.03)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
I(LTV>=80%)	-0.81***	-0.06***	-0.81***	-0.05***	-0.80***	-0.04***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
I(LTI>=4.5)	-0.16***	-0.00	-0.16***	-0.00	-0.16***	-0.01**
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)
I(LTI>=5.5)	-0.82***	-0.04***	-0.82***	-0.03**	-0.82***	-0.03**
	(0.04)	(0.01)	(0.04)	(0.02)	(0.04)	(0.01)
I(Refinancing)	-0.09***	-0.03***	-0.09***	-0.03***	-0.09***	-0.03***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Ln(Total Assets)	0.05***	-0.04***	0.02	-0.03***	0.04**	-0.06***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
Mortgages/TA	0.01***	-0.00***	0.01***	0.00**	0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Deposits/TA	-0.01***	-0.00	-0.01***	-0.00***	-0.01***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity/TA	0.04***	0.02***	0.04***	0.01***	0.05***	0.02***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
I(2nd Semester)	-0.10***		-0.11***		-0.05***	
	(0.02)		(0.02)		(0.02)	
Constant	0.02	1.30***	0.87***	0.61***	0.48**	1.15***
	(0.24)	(0.04)	(0.24)	(0.04)	(0.23)	(0.04)
Observations	25'125	25'125	25'125	25'125	25'125	25'125
Year*Month FE	No	No	No	No	No	No
Lambda	0.16***	0.16***	0.15***	0.15***	0.16***	0.16***

Columns with unequal numbers display the Heckman first stages, probit regressions of whether the bank's response is an offer on the same regressors as in Tables 1 and 2 plus an indicator for whether the response was sent in months 7-12 rather than 1-6 of the year. Even columns show estimates of the main equation controlling for the non-selection hazard. For reasons of software capacity, Columns 3-8, which control also for household fixed effects, implement this as a two-step procedure. By contrast, Columns 1 and 2 must use household controls instead of fixed effects to avoid collinearity with the competition measures of interest. Without household fixed effects, estimations can be implemented through Maximum Likelihood Estimation (MLE), which improves estimator efficiency. Standard errors clustered by bank * household zip in parentheses. * p<0.1, ** p < 0.05, *** p<0.01.