# A FinTech matching mortgage lenders with borrowers online and bank competition, diversification and automation opportunities

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*How do banks offer mortgages through on online platform to areas without their branch presence? Unique data on responses from different banks to applicant households yield three salient findings: First, banks offer 4% more often and 6 basis points cheaper credit when markets have high versus low concentration, implying more profitable future business. Second, they offer 2% more often and 2 bps cheaper credit when unemployment or house price growth in the applicant's state are one standard deviation less correlated with those at home, improving portfolio diversification. Third, these offers are increasingly automated, using available hard information more efficiently. (99 words)*

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## 1 Introduction

We analyze how banks choose offer propensity and pricing in response to mortgage applications when an online platform, together with hedonic models of collateral appraisal, allows them to make offers to clients from across the country. Through the platform, each bank can offer also to clients in regions where the bank lacks branches, reputation, staff, and/or local expertise. Unique data on responses from different banks in different locations to each applicant allow us to study how the same bank responds to different customers, and how the same customer receives responses from different banks. We link bank responses to the concentration of each local market and to the extent to which each individual mortgage would contribute to each bank's own geographical diversification.

Our findings on how online pricing of mortgages relates to local competition extends an emerging literature on how the internet changes competition (e.g., Cavallo (2017); Gorodnichenko and Talavera (2017)) to the financial sector. Studying mortgage lending in particular is warranted by the fact that a mortgage borrower's location matters for the lender not only because of inter-regional differences in competition, but also because of inter-regional differences in default probabilities and collateral values. Once freed from brick and mortar legacies through internet lending, banks' possibilities for geographical diversification are extended beyond those through securitization or bank holding companies, both of which the financial crisis showed to be burdened by agency problems.[1]

We exploit data from the Swiss platform Comparis.ch, where between 2008 and 2013 households could apply for mortgages and received responses from many different banks. Beyond breaking down historical legacies of geography, this financial technology or FinTech platform yields data that have two major advantages for research. First, we observe both 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. Second, we observe for each application not just the response from one,

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

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. If we observed only completed contracts, then banks from other cantons (Swiss federal states) might have attracted only low-risk (along unobservable dimensions we cannot control for) clients keener to contact also lesser-known banks to fully exploit their good credit-worthiness, or they might have attracted only high-risk clients who failed to get a good offer at local banks. On the platform by contrast, each household gets offers from both local and distant banks so that we can directly compare the offers within the same client. Following pioneering work by Khwaja and Mian (2008), this methodology has been applied more recently by many papers on bank lending to firms with more than one bank relationship (e.g., Jiménez et al. (2012); Chodorow-Reich (2014)). In contrast, it is less common for households to maintain 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 mostly elusive and achieved for lending to households only by Basten (2020) using the same data, and by Michelangeli, Peydro and Sette (2019) who sent randomized simulated mortgage applications to different banks.[2]

To identify the causal effect of each state's prior market concentration on banks' online responses, we exploit changes in local concentration caused by overseas (US subprime) losses of Switzerland's big two banks UBS and Credit Suisse (CS). As a result of these losses, the two banks had to significantly cut domestic mortgage lending, thereby reducing local market concentration more the larger their prior market share in each canton. Exploiting prior variation in exposure to exogenous supply shifts, as previously done by, e.g., Mian and Sufi (2012), Chodorow-Reich (2014) and Gete and Reher (2018), is particularly clean in our setup as US losses of UBS and CS are quite exogenous to later online bids of small Swiss banks that have no noteworthy US exposure. In particular, neither of the two big banks participated in the platform we analyse: They already had branches everywhere and presumably did not need to use the platform. So the setup satisfies the requirements of exogenous shifts for shift-share or

[2] More recently, Chava et al. (2020) and Garber et al. (2020) also analyze behavior of different banks *vis-à-vis* the same household, focusing on credit card debt in the US and Brazil, respectively.

Bartik (1991) instruments, as recently discussed by Borusyak, Hull and Jaravel (2018) and Goldsmith-Pinkham, Sorkin and Swift (2020).[3] Overall, we obtain three salient findings.

First, we find that on the web banks make more and cheaper offers to applicants from previously *more* concentrated (*sic*) markets. This may at first seem surprising when considering the mortgage as a one-off business. Then we might have expected the exact opposite, with banks lowering prices only when offering to less concentrated markets. However, offering lower prices instead to more concentrated markets allows banks to enter new, more profitable markets given customer switching costs. Households thus obtain better offers.[4]

Second, going beyond banks' responses to prior local competition, we find that banks seize the online channel in particular to lend more to regions where past unemployment rates as drivers of default probabilities and past house price changes as drivers of loss given default have been less correlated with those in the bank's home canton. This allows banks to improve the risk management of their mortgage portfolio. Both our findings on competition and those on risk management considerations survive at least as strong when in our robustness checks we combine them. Therefore our baseline analyses consider both dimensions separately so that we can always use the most conservative set of controls, give both topics sufficient attention, and connect to different strands of the literature.

Our findings on regional diversification contribute to a by now extensive literature that exploits the US interstate bank deregulation following Jayaratne and Strahan (1998) and as evidenced by Goetz, Laeven and Levine (2013), Goetz, Laeven and Levine (2016) and references therein. While Goetz, Laeven and Levine (2013) find increases in regional diversification to have reduced average stock market valuations of US bank holding companies, Goetz, Laeven and Levine (2016) find that it did nonetheless overall reduce bank riskiness as measured by the standard deviation of bank stock returns as well as the Z-score and other risk measures. They argue that the hedging of idiosyncratic local risks dominated potential

[3] We discuss below that our estimates are robust to computing standard errors with a correction for possible correlations of residuals between regions with similar Bartik shares, as recently recommended by Adão, Kolesár and Morales (2019).

[4] These findings contribute also to the literature on how distance and technology affect the degree of competition in banking (Petersen and Rajan (2002); Degryse and Ongena (2005); Degryse, Laeven and Ongena (2009); Eichholtz et al. (2020)), showing that the role of distance is modified as bank lending moves online.

reductions in banks' ability to monitor loans located at a larger distance. While their risk measures cover banks' entire balance sheets, including loans to firms and other assets, we focus on how banks can better diversify specifically their mortgage portfolios. Through an online platform like the one studied here, lending decisions for different regions can still be made by the same central decision-maker, removing the agency problems between bank headquarter and local credit officers traditionally associated with larger distance. The online platform analyzed may thus reduce agency costs even beyond the level analyzed by Berger and DeYoung (2006), who saw reductions in distance-related agency costs within US bank holding companies through improvements in information processing and telecommunication.[5]

Third, after having estimated how banks' offer and pricing decisions depend on market concentration, portfolio complementarity and other household and bank characteristics, we use a model with multiplicative heteroscedasticity (Harvey (1976)) to explore which bank responses are more automated around rules and so contain less discretion. We find less discretion for safer applications, as well as by larger or more mortgage-focused banks. We also find discretion to decrease with the number of online responses a bank has already sent out, allowing to reduce operational costs and use the available hard information more efficiently (see also, e.g., Berg et al. (2019)). We so bring together the literature on rules vs discretion in banking (e.g., Cerqueiro, Degryse and Ongena (2011); Cerqueiro, Degryse and Ongena (2013)) with the recent literature on how the internet changes price setting (Cavallo (2017); Gorodnichenko and Talavera (2017); Gorodnichenko, Sheremirov and Talavera (2018)). Gorodnichenko and Talavera for example 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 show empirically that this leads to more frequent price adjustments. Swiss mortgage prices have low frictions of price adjustment also offline, as each client receives an offer customized to his or her particular risk characteristics and willingness to pay. But search costs are lowered and geographical barriers removed when lending moves to the type of online platform we study.

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

More widely, our paper contributes to the emerging literature on how financial technology or "FinTech" changes financial intermediation. We refer to Thakor (2020) who defines FinTech as "the use of technology to provide new and improved financial services".[6] Of the four uses of this technology listed by Thakor, our paper focuses mostly on the lowering of search costs of matching transacting parties. Our setup also fits well with the more recent alternative definition of FinTech by Allen et al. (2020) as brokerage rather than dealership, i.e., of lending without taking the loans onto the own balance sheet. By contrast, Buchak et al. (2018) consider only FinTechs simultaneously defined as shadow banks in the sense of non-depository institutions. In this paper we focus on the activity rather than on who carries it out, as the type of online platform we study may be organized by a non-bank as in our case, or may be taken over by a bank and yet have much the same effects.[7] Finally, Fuster et al. (2019) recently emphasize that FinTechs can address market frictions. Consistent with this, we show the online platform studied to specifically address frictions from geography. It gives borrowers access to more possible lenders, which bears some analogies with recent findings in Bartlett et al. (2019) on how FinTech has improved access to mortgages for minority groups in the US.

Beyond allowing in particular borrowers from more concentrated local markets to obtain more and better offers, and allowing banks to better diversify their portfolio and lower operational costs, mortgage contracting through an online platform does of course have the benefit of being possible also during pandemics like the recent Covid pandemic, when physical contact is more limited.

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

[7] 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, 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 .

## 2 Hypotheses

In this section we develop hypotheses on how bank responses vary with respectively prior local market concentration and the potential for regional diversification. Following this, we also develop three hypotheses on the extent to which lending and pricing decisions are automated.

### 2.1 Hypothesis on Local Market Concentration

Our main interest is in how banks' online offer behavior responds to how concentrated the mortgage market in the applicant's region has been so far. In the basic oligopolistic version of the well-known Monti (1972)-Klein (1971) model (see, e.g., Freixas and Rochet (2008)) banks optimize lending and deposit business separately, then lend or borrow any difference between loan and deposit volumes in the interbank market. And they do so for a single period only. In such markets, we might expect banks to demand *higher* prices the *more* concentrated the market they are offering to.

But on the other hand, and potentially more realistically, clients in retail banking buy packages of services from the same bank including several components of mortgage loans, mortgage loan refinancing, deposit accounts, transaction accounts, or investment advice. This allows banks to "cross-sell" products. One key reason why customers do not shop around afresh for each 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, Fischer (1990), Sharpe (1990), Rajan (1992), and von Thadden (2004) point out that lending requires the bank to make some upfront investment into screening and monitoring the client. But this 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.[8] Thus we expect that online lending is particularly attractive to banks when it allows them to win a new client in a so far more concentrated market where the bank expects more profitable future business. So we posit:

*Hypothesis 1 (null):* *Banks are* ***less*** *likely to offer, and offer* ***higher*** *prices, the more concentrated the local mortgage market has been so far.*

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

### 2.2 Hypotheses on Risk Management

Degryse and Ongena (2005) analyze the role of distance between banks and borrowing firms from a competition angle. They find banks to charge higher prices to less distant firms, consistent with similar findings by Petersen and Rajan (2002) 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. Given these findings, we might *prima facie* expect offered lending margins to decrease in distance also in our setup. But the financing of owner-occupied residential property in Switzerland differs from that of firms along at least two relevant dimensions. First, 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 practically ruled out in Switzerland through prohibitive pre-payment fees. Second, 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, real estate is by definition immobile and its value therefore intimately tied to economic

[8] 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 deposits per se loss-making, yet banks were found to prioritize retaining depositors for future profits.

conditions at its location. So we include analyses on the complementarity of borrower and lender location, correlated with distance, under the topic of risk management rather than competition.

In particular, a bank can reduce risks to its mortgage portfolio by allocating more of its new lending to regions where default rates or collateral values are less correlated with those at home. In this vein, Quigley and Van Order (1991) 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.

On the other hand, a bank's risk managers may instead prefer to focus lending on fewer regions so that it pays to collect more information there. This argument is made by Loutskina and Strahan (2011) and empirically confirmed for the US market. Further, Favara and Giannetti (2017) show that a bank with many mortgages in the same region can better internalize the negative externalities of collateral liquidations on the prices of other nearby collateral in an episode of increased defaults, and likewise Giannetti and Saidi (2018) find an internalization of spill-overs from the liquidation of firm loans in more concentrated industries. This per se would speak in favor of seeking to sufficiently dominate one area in order to internalize and therefore ideally remove that externality. Finally, Agarwal and Hauswald (2010) show that banks find it easier to screen firms located closer to them, which is typically where a bank has already done most lending in the past. In the same vein, Eichholtz et al. (2020) find US banks to add margins increasing in distance when pricing mortgages underlying Commercial Mortgage Backed Securities. They 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, Laeven and Levine (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, Laeven and Levine (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 (2002).

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. (2020). Therefore the context complies very much with one characterized by Stein (2002) 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. So we expect the diversification motif to dominate and posit:

*Hypothesis 2:* *Banks are more likely to offer, and offer lower prices, when unemployment rates as proxies for default probabilities, or house prices as collateral values, have historically exhibited a* ***lower correlation*** *between the applicant's and the bank's canton.*

### 2.3 Hypotheses on Automation

Any of the determinants of mortgage pricing discussed above 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 platform and would therefore expect less heterogeneity in offers than in contexts in which loan officers may dispose of additional soft information. Yet we do expect more scrutiny for riskier applications as well as by banks who have less (offline) experience in the mortgage market because they are smaller or less focused on the mortgage business.

More interestingly in the context studied, we expect that banks can increasingly automate their business the more experience they have already accumulated with lending through the platform. So we posit:

*Hypothesis 3: We expect* ***more discretion*** *for responses (a) to* ***riskier*** *applications, (b) from* ***smaller or less mortgage-focused*** *banks, or (c) submitted when banks have so far* ***less web experience****.*

## 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.[9] For reasons of data quality, we focus on 2010-13.

The resulting data are unique and offer at least five advantages for our analysis. First, we separately observe demand and supply. Second, banks in their operation and we in analyzing them can rule out differential access to clients from different regions based on amongst others pre-existing branch networks. Third, we can rule out that different banks tend to interact with different types of clients. Fourth, we observe 100% of the information each bank also has on each client. Bank decisions cannot be biased by the use of soft information acquired through prior personal interaction. Furthermore, as banks do not learn applicants' names, they must rely on the information we fully observe and cannot complement it e.g. with external credit scores. Fifth, in contrast to many brokers who earn differential fees from different lenders (Robles-Garcia (2019)), the platform analyzed was paid by borrowers only.

Observations on how different banks respond to the same client have to the best of our knowledge until recently been achieved only in research on lending to corporates. In contrast, households engaged in mortgage borrowing have not been observed to interact with several different banks. Yet Jordà, Schularick and Taylor (2016) and other papers have shown forcefully the importance of the key role of

[9] In an Online Appendix we document how borrowers and lenders on the platform we study are representative for the full national market.

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. And endogenous matching is likely to matter also for our questions of interest, because offline the type of households willing to contract with distant banks is likely to differ from the type who stay with local banks only. To our knowledge the first paper to observe how different banks respond to the same mortgage borrower is Basten (2020) who uses the same 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 and Mariathasan (2018) and Basten (2020). 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.[10] Prices offered here are indeed a key dimension along which banks can influence how many mortgage contracts they conclude each period. Thus Basten (2020) shows, using the same data, how banks more affected by higher capital requirements increase offered mortgage rates more and thereafter end up with lower growth rates in their mortgage volumes. Important to emphasize when we analyse how offers are related to i.a. local market concentration is the fact that in Switzerland banks can and do offer customer-specific rates, like in the US or Germany and unlike for example in the UK where Robles-Garcia (2019) reports banks to offer practically the same rate to every customer with the same fixation period and LTV.

[10] 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.

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. Finally, to construct our instrument we use data on the two big banks' shares in cantonal markets, which can be computed from data on the SNB website.[11]

### 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 a bit under 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 a mean close

[11] See https://data.snb.ch/.

to CHF 170’000, wealth including pension fund wealth reached an average close to CHF 500’000, and average age was 46 years.

Next, Table 1 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 0.12 and 0.49, with a mean of 0.18 and a standard deviation of 0.05. The multi-market contact (competition) measure (MMC) of how many competitors in a canton a bank meets on average in how many other cantons ranges between 0.05 and 0.40 with an average of 0.07, while the number of online providers varies across cantons between 4 and 14, with an average close to 11. Finally, we see that house price growth rates vary between -4% and +15% with an average around 4%, while the share of foreigners varies between about 10 and 40%, with an average of about 21%.

Looking at bank characteristics in Table 1 Panel (C), where banks are again weighted by the number of responses sent out, total assets (TA) range between CHF 434 million and CHF 37.8 billion, with an average of 16.9 billion. These numbers reflect that the platform did not feature any of the banks with a nation-wide branch network such as UBS and CS, given that UBS’ total assets in 2010 were about CHF 1.3 trillion and those of CS about CHF 1 trillion. Rather the platform was used primarily by so far more local banks who could benefit from reaching new regions through the platform. Between about 40% and 91% of these assets, and on average 70% of them are invested in mortgages, which reflects the general focus of Swiss retail banks 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.

Table 1 Panel (D) finally gives the key characteristics of bank-household interactions. First, when sending out each response, banks could draw on experience with between 0 and about 10’000 prior responses, with an average of about 4’000 as not all banks ever reach the 10’000 during our sample period. Relevant for portfolio diversification, the inter-cantonal correlation of unemployment rates was on average 92%, but goes as low as 66% and has a high standard deviation of about 68%, suggesting that there is still potential to lower correlations in the portfolio overall. The inter-cantonal correlation of house price changes achieves a mean of 77% with a standard deviation of 19%, but which goes as low as 15%. This reflects the fact that while real estate markets in all cantons are affected by the same interest rate, net immigration differs considerably due to different languages and therefore different source country compositions, as does regional economic specialization. Further, responses take 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 (FP) 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 FP. The average rate offered amounts to 2.16%, which implies an average spread above the swap rate for the same period of 90 basis points (bps). Yet the spread varies between 40 and 152 bps, so banks' eagerness to win a deal varies significantly.

## 4 Empirical Strategy

We organize our analyses around the areas covered in our hypothesis section above: market concentration, risk management, and automation. After explaining how we tackle each of these three areas, we discuss how we combine non-linear estimators with both instrumental-variable methods and a large set of fixed effects, as well as how we compute our standard errors.

### 4.1 Strategy on Local Market Concentration

Our key measure of the concentration of cantonal mortgage markets is the Herfindahl-Hirschmann Index (HHI), i.e. the sum of squared mortgage market shares, in cantonal mortgage volumes.[12] One issue is that when analyzing the effect of prior market concentration in the applicant's canton, we can — other than in the analyses on inter-cantonal unemployment and house price correlations discussed below — not exploit variation within literally the same applicant. It is then possible that different banks' prior presence as well as current online offer behavior are influenced by the same unobservable. In that case,

[12] Not only do we not have all data for regions more granular than the 26 cantons, but cantons are also considered separate but entire markets by 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.

any estimates of more or better offers to previously more concentrated cantonal markets constitute only a *lower bound* on banks' true eagerness to enter those markets, for they might be even more eager to lend there keeping fixed unobserved disadvantages of that region which might have reduced banks' prior offline presence and thereby led to a more concentrated market.

To address this concern, we exploit the fact that precisely during the years of interest most Swiss cantonal mortgage market concentrations fell, after the "big two" banks UBS and Credit Suisse (CS) had experienced drastic losses in the US market and suffered hefty subsequent deposit withdrawals by their Swiss customers. As a consequence, their Switzerland-wide mortgage portfolios ended up growing only about half as fast as that of the market as a whole. This opened up opportunities for other banks and it did so more the larger the initial market share held by the big two banks. We instrument the actual HHI in each year and canton by that predicted by this exogenous change only. In particular, we compute the predicted HHI as the 2009 level plus the Switzerland-wide changes, and weight these changes by the big two banks' 2009 market shares.

This strategy to exploit pre-existing variation in market shares to obtain differential exposure to a supply-side shock is similar to strategies recently used by Mian and Sufi (2012), Chodorow-Reich (2014), D'Acunto and Rossi (2017), and Gete and Reher (2018). Chodorow-Reich in particular discusses also how Credit Suisse was hit hard by losses in the US mortgage backed securities market and therefore had to reduce amongst others its US syndicated lending. In contrast to those papers which focus on effects of losses or higher costs in the US on some segment of US lending argued to be sufficiently exogenous, we exploit the fact that following their losses in the US the Swiss Big Two had to cut also their lending at home, which reduced market concentration in particular in those cantons (states) where the two had the largest market shares before.

The episode and its exogeneity to Swiss mortgage markets is discussed in more detail in Blickle (2018) and Brown, Guin and Morkoetter (2020). The latter paper analyzes which types of households were how quick to withdraw deposits from the big banks. Blickle exploits that where the Raiffeisen network of cooperative banks had branches close to UBS branches significant portions of the deposit outflows from

UBS went to Raiffeisen and enabled it to increase their mortgage lending. 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 banks without overseas losses or deposit withdrawals were limited, the Swiss National Bank (SNB) orchestrated an opportunity for them to issue additional covered bonds and so borrow against collateral through the so-called "Limmat transactions" in 2008 and 2009.[13] 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.[14] Yet given capital constraints new lending was not a priority, especially for mortgages where the relationship component was arguably less important.

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 competition intensity in cantons in which these two big banks had previously been serving a larger share of the market. First, clients seeking to refinance a mortgage typically ask first for refinancing conditions with their existing lender. Second, 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 so reduced the HHI of market concentration.

As pointed out recently in the economics literature by Borusyak, Hull and Jaravel (2018) and Goldsmith-Pinkham, Sorkin and Swift (2020), the validity of a Bartik or shift-share instrument requires that either shares or shifts or both are uncorrelated with the outcomes of interest through channels other than the instrumented variable. In our setup it is not clear that this exclusion restriction would hold for the *shares*, for we cannot exclude the presence of some unobservable which affects both the big two banks' prior market shares and other banks' current online bidding behavior. However, the *shift* caused by the big two banks' losses in the US market is plausibly not otherwise related to smaller Swiss banks' differential online bidding. In particular, the Big Two whose overseas losses a few years earlier trigger the shifts in

[13] For more details, see https://www.fuw.ch/article/der-stille-retter-der-grossbanken/ , accessed on October 23, 2019.
[14] See e.g. https://www.theguardian.com/business/2008/oct/16/ubs-creditsuisse accessed on October 23, 2019.

local cantonal market competition are not part of our sample. Instead our sample focuses on the behavior of local banks with no noteworthy exposure to US subprime markets in earlier years.Our baseline regression can be summarized as follows:

$$Y_{h,b} = \alpha + \beta(HHI_h) + \delta X_h + \mu X_b + \tau(YMFE_h) + \varepsilon_{h,b} \tag{1}$$

Here subscript $h$ denotes the household and subscript $b$ the bank. Baseline regressions for the binary outcome $Offer_{h,b}$ are estimated by Probit, those for the continuous outcome $Pricing_{h,b}$ by linear regression. In both cases, we instrument $HHI_h$ with changes in cantonal competition intensity induced by the Big Two overseas losses as explained above. We start with both bank and household controls, then replace bank controls $X_b$ with bank fixed effects, and finally also replace household characteristics $X_h$ with household group fixed effects. Groups capture every household characteristic except for the canton of residence, which would be collinear with the HHI regressor of interest. In variants one and two with household controls, we additionally control for year*month fixed effects. In the third variant with household fixed effects, year*month fixed effects are nested within the household fixed effects.

In our Online Appendix Table 9, we also test the robustness of our estimates to correlations of residuals across regions with similar Bartik shares as recently recommended for Bartik or shift-share designs by Adão, Kolesár and Morales (2019). We find that in our case standard errors do not become larger when doing so.

### 4.2 Strategy on Risk Management

As we do not directly observe inter-cantonal correlations between actual mortgage market *losses*, we use instead correlations between unemployment rates as drivers of probabilities of default, and in year-on-year changes in house prices as key determinants of loss given default. The use of house price change correlations has the benefit of taking into account not only house price collapses in the last crisis in the early 1990s but also house price growth since then, which banks may consider to paint a more up-to-date picture. These 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 subject to the same monetary policy it is hard to find a region whose house prices can be expected to *increase* when those elsewhere *decrease*. Yet despite a common monetary policy, summary statistics show that as different cantons specialize in different economic sectors and receive the majority of net immigrants from different countries, some inter-cantonal correlations are as low as 0.15, which does allow for diversification. We can thus summarize our analyses of banks' responses to geographical complementarity as follows:

$$Y_{h,b} = \alpha + \beta(Complement_{h,b}) + \delta X_h + \mu X_b + \tau(YMFE_h) + \varepsilon_{h,b} \quad (2)$$

In general this follows the specifications in Equation 1 on market concentration, except that the primary regressor of interest is now our measure of portfolio complementarity instead of the HHI competition measure. As complementarity varies both within households and within banks, we can now use fixed effects for each household rather than just for each household group. Therefore we do now not need to find a suitable instrument for the complementarity regressor.

### 4.3 Strategy on Automation

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

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

$$\ln\left(u_{h,b}^2\right) = \alpha + \beta X_h + \gamma X_b + \delta(HHI_h) + \theta(Complementarity_{h,b}) + \mu(Experience_{h,b}) + \varepsilon_{h,b} \quad (3)$$

These include again all household characteristics $X_h$, all bank characteristics $X_b$, market concentration in the applicant's canton $HHI_h$ and $Complementarity_{h,b}$ between household $h$'s and bank $b$'s canton. In addition, we now include $Experience_{h,b}$, measured by the number of responses bank $b$ has already sent out when responding to household $h$. As before we start by including all bank and household characteristics as expressed in Equation 3. In subsequent variations, we first replace bank chacteristics with bank fixed effects and then replace also household controls with household group fixed effects. While econometrically mean and variance equation may contain different sets of regressors, so that existing papers denote regressors in stage 2 by Z instead of X, we use the same sets in both stages.[15]

### 4.4 Nonlinear Estimation with Endogenous Regressors and Fixed Effects

To probe the robustness of our results, our tables on competition and risk management start out in columns 1 and 2 with both bank and household controls, replace in columns 3 and 4 bank controls with bank fixed effects, and replace in columns 5 and 6 also household controls with household (group) fixed effects. While columns 2, 4 and 6 use as outcome of interest the continuous variable pricing and can thus be estimated linearly, columns 1, 3 and 5 use the binary outcome Offer, which calls for a non-linear probit or logit estimator. The probit estimator we use in columns 1 and 3 can be combined with bank fixed effects without running into the incidental parameter problem, as we have merely 26 different banks and on average more than 4'200 observations per bank. By contrast, in Column 5 which includes fixed effects for each household (group), we would have too few observations per cross-sectional unit so that a probit estimator would not be consistent (Greene (2004)). Therefore column 6 always uses

[15] Following Harvey (1976) we use Maximum Likelihood to improve estimator efficiency.

instead a logit estimator, which following Abrevaya (1997) can be implemented as conditional Maximum Likelihood Estimator and thereby circumvent the incidental parameter problem.

The move from probit to logit in column 6 in turn means that implementing the instrumental variable (IV) method through predictor substitution, i.e. by replacing in stage 2 the endogenous regressor with its predictor obtained in the first stage, is inconsistent. Following Terza, Basu and Rathouz (2008) however, a consistent estimator can still be obtained by implementing the IV method through residual inclusion. Here stage 2 does include the endogenous regressor itself, rather than its predictor, but it controls in stage 2 for the residuals from stage 1.

### 4.5 Standard Errors

Following Bertrand, Duflo and Mullainathan (2004), at the baseline we cluster our standard errors by the panel dimension of columns 5 and 6 of each table, i.e. by the 708 household groups for our market concentration analyses and by the 6'914 households for our risk management analyses. Robustness checks available on request, which cluster instead by the 7'442 bank * household zip code combinations, or by the 173 bank * household canton combinations, yield qualitatively the same results. All of these options have more than 50 clusters as recommended by Cameron and Miller (2015) and none of them contains more than 5% of observations, as recommended by Rogers (1993), both guidelines of which are violated if we cluster by the 26 banks or 26 cantons only. Yet for completeness and as we briefly discuss later our Online Appendix probes also that, once without and once with bootstrapping standard errors (Cameron, Gelbach and Miller (2008) and Roodman et al. (2019)) and finds the coefficients of interest to be significant also then. Likewise when we follow Adão, Kolesár and Morales (2019) and account for possible correlation of residuals between regions with similar Bartik shares in our instrumental variable strategy on competition.

## 5 Results

Table 2 and Table 3 present our baseline results on market concentration, Table 4 focuses on risk management through geographical diversification, and Table 5 looks at automation. In addition, a wide range of robustness check tables is available in the Online Appendix, but also briefly discussed below. To facilitate comparison, all tables follow a similar structure, analyzing in columns with unequal numbers whether each of the 25'125 bank responses constitutes an offer or a rejection, and in columns with equal numbers the spread above maturity-congruent refinancing costs offered on the 20'583 offers. Results on offer propensities are robust to using logit or a linear probability model (LPM) instead of probit regressions. Furthermore, columns 1-2 always start out with both household and bank controls, columns 3-4 replace bank controls with bank fixed effects, and columns 5-6 replace also household controls with household fixed effects in analyses on risk management, while the analyses on responses to market concentration use instead fixed effects for household groups which consist of all characteristics except for geography to avoid collinearity with canton-varying market concentration. The tables show the regressors of specific interest in those tables at the top, followed first by key household characteristics and then by key bank characteristics.

Before discussing more deeply banks' responses to market concentration and portfolio complementarity, we start by briefly discussing their responses to households' and banks' own characteristics, which are shared by all tables and help to better understand the setup. For household characteristics we focus on indicators for LTV ratios above 67% and 80% and loan-to-income (LTI) ratios above 4.5 and 5.5 respectively. The specific threshold values reflect frequent practice in the market;[16] while 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 (2020)). The threshold indicators turn out to have stronger effects on the outcomes of interest than continuous LTV or LTI variables. In robustness checks available on request, continuous LTV and LTI ratios fail to have a statistically significant effect on our outcomes of interest after controlling for the indicators displayed here. Furthermore, in line with common practice at

[16] 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.

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

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 have shorter contractually guaranteed rate fixation periods. Thus financing mortgages – the majority of which carries fixed rates – with deposits tends to yield a profitable margin in the short run, but implies also more interest rate risk to be borne or hedged at a cost. 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 safety in crisis times but also) higher marginal costs per unit of lending. After this general discussion on the effects of our control variables, demonstrating the validity of our setup, we now turn to our key regressors of interest.

### 5.1 Results on Local Market Concentration

*Main Findings*

Table 2 looks at banks' responses to local market concentration 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 0.12 and 0.49, reflecting the heterogeneity of cantonal markets, and amounts to 0.18 on average.[17] Read literally, coefficients in Table 2 address the effects of offering to a so far fully monopolized market (HHI = 1) rather than a fully competitive market (HHI = 0). In particular, below the constant we display in columns 1, 3 and 5 the average (across all observed HHI values) marginal effects implied by our probit and logit coefficients. They show that a bank would be 18-35% more likely to make an offer to a fully monopolized market and in addition be willing to discount the price by 50-57 bps. More realistically, the 0.10 HHI difference between low and high concentration by the definition of the US Department of Justice would increase the offer probability by 1.8-3.5% and in addition lower the price by 5-5.7 bps.

Table 3 explores further the plausibility of our interpretation (along the alternative for Hypothesis 1) whereby banks make more and cheaper offers to cantons with higher market concentration with the motivation to land more lucrative future business there. In this vein, we added interactions of the HHI with respectively an indicator of whether the household's age exceeds the 25$^{th}$ percentile of 38 years, with an indicator for whether the applicant asks to finance a new purchase, with the share of foreigners in the applicant's canton in 2010, and with an indicator for whether the amount asked for exceeds the 90$^{th}$ percentile or CHF 1 million. The reasoning behind these tests is that ceteris paribus a bank can expect more lucrative future business from younger households, new mortgage borrowers, foreigners new to the country, or borrowers of larger sums. Each of the interactions is instrumented with the interaction of the respective household characteristic with the instrument for HHI, which is valid under

[17] By way of comparison, the US Department of Justice (DoJ) classifies markets with HHI below 0.15 as having a low and markets with HHI above 0.25 as having a high concentration, see https://www.justice.gov/atr/herfindahl-hirschman-index.

the assumption that the respective household characteristics are exogenous to current bank offer behavior.

To start with, while the main effect of age tells us that a household aged below 38 pays on average 4 bps extra given larger uncertainty about credit-worthiness, the HHI discount increases from 36 bps (42 with all fixed effects) to 54 (60 with all fixed effects). This plausibly reflects that a younger household is likely to bring in more new business not already at other banks. Similarly, while per se new mortgage clients are charged about 7 bps extra to account for their shorter repayment history, the HHI discount is up to 24 bps larger for them, consistent with the fact that winning a new client over once does also increase the bank's chances to provide later refinancing. By contrast, the share of foreigners in the applicant's canton has no significant effect, which may reflect simply that the share of foreigners per canton is a rather crude proxy for whether or not the household itself is new to the country and which neither we nor the banks can observe. Finally, we observe a discount of between 17 and 24 bps for mortgages of at least CHF 1 million, but with our clustering that effect is statistically significant only at the 10% significance level, and only in one of our three specifications. Relatedly, for all interaction terms we observe no statistically significant effects on offer propensities, but only on pricing. But the effects of the interactions between HHI and the dummies for respectively young households and first-time buyers on pricing are consistent with banks exploiting the platform to start new business in particular with expectedly more lucrative new clients.

*Robustness*

Looking at Table AT1 and Table AT2 in the Online Appendix, where the impact of big banks' retraction is translated to cantons on the grounds of their previous deposit rather than mortgage market shares, we find overall qualitatively very similar results, which is not surprising as 2009 big two shares based on deposit volumes (Table AT1) or deposit account numbers (Table AT2) are 90% (86%) correlated with shares based on mortgage volumes. Correspondingly, Table AT3 there shows that, across all three methodologies, regressing actual HHI levels in the year of the bank response on HHI levels predicted with the shift-share instrument yield coefficients between 0.85 and 0.88 when using bank and household controls or bank fixed effects and household controls, and between 0.96 and 0.97 when using both bank and household group fixed effects.

When, for comparison, Table AT4 uses basic OLS rather than IV regressions, the average marginal effect on offer propensities, displayed at the bottom, shrinks from 18 to 13, 28 to 14, and 35 to 28% in the three specifications respectively, and remains statistically significant only in the versions with fixed effects rather than household and bank controls. Likewise the effect on pricing in the three specifications shrinks from 54 to 34, from 57 to 44 and from 50 to 49 bps respectively. This confirms our argument above that absent exogenous variation in prior market concentration effects tend to be downward biased. Our IV strategy solves this and finds true effects to be larger.

In contrast to our IV regressions, which cannot instrument both HHI and another measure of market concentration, Table AT4 includes also the measure of Multi-Market Contact (Competition). It finds that if anything banks tend to offer more often (column 3) and at lower prices (columns 2 and 4) if they encounter in a market more competitors whom they meet also in other cantons. This is more consistent with the findings in Park and Pennacchi (2009) whereby multi-market contact promotes more competitive behavior than with the earlier idea of Edwards (1955) of a "linked oligopoly".

Table AT5 repeats our Bartik (1991) instrumental variable estimates of the effect on local market competition on pricing by probing each of the three sets of controls (columns 1-3, 4-6, and 7-9 respectively) with each of three different methods of computing standard errors. While columns 1, 4 and 7 use our baseline methodology clustered by household group, columns 2, 5 and 8 use the "AKM0" and 3, 6 and 9 the "AKM" procedure described in Adão, Kolesár and Morales (2019).[18] We do not find standard errors to become significantly larger in our setup. Relatedly, Table AT6 repeats the same

[18] We focus this robustness check on the outcome pricing, as the outcome offer is binary and the AKM computation is not currently available for non-linear estimation methods.

estimations but clusters standard errors by the 26 cantons rather than by the 708 household groups.[19] Once more the estimates remain most similar.

Table AT7 repeats the same estimations but uses a Herfindahl-Hirschmann Index (HHI) of market concentration which is based not on banks' shares in mortgage stocks on their balance sheets, but instead on their shares in all cantonal bank branches.[20] The results confirm those in Table 2 and in some cases the estimates are even slightly larger, implying that results do not hinge on a particular way of measuring market concentration.

Last, we foreshadow here that the results on banks' responses to prior market concentration are overall equally clear and for pricing even stronger when in Table AT10 in the Online Appendix we analyze them simultaneously with those to risk management incentives, as discussed in more detail below.

### 5.2 Results on Risk Management

*Main Findings*

As per our *Hypothesis 2*, Table 4 analyzes how banks' responses relate to the complementarity of unemployment rates in the applicant's canton with that in the bank's home canton, which typically makes up the majority of mortgages already on the bank's balance sheet. The complementarity is simply the inverse of the correlation, scaled between -1 and 1. Higher complementarity values imply lower correlations, so unemployment as the key systemic driver of defaults in the applicant's canton increases less when those in the bank's home canton increase.[21] As in Table 2 and 3, columns 1, 3 and 5 for the binary outcome offer display first the probit (logit) coefficients for all regressors, and below the constant we then display the associated average (across all observed values of complementarity) marginal effects.

[19] Given the small number of clusters in this case, we follow Cameron, Gelbach and Miller (2008) and Roodman et al. (2019) in re-computing at the bottom of the table the p-values for the coefficients of interest on HHI also using wild bootstrapping. With and without bootstrapping, the coefficients remain statistically significant at least at the 5% level, except for that in Column 1, where the P value increases to 16%. As the specifications with fixed effects seem more credible to us anyway, we take this to confirm that our estimates of interest are robust to how we compute standard errors.
[20] Even with the advent of phone- and internet-banking, market concentration measures based on deposits, loans and branches remain significantly correlated. Of course this correlation is being undermined by the phenomenon we investigate. Another drawback of this measure (which is based on branch presence in the phone book) is that we currently have access to it in digital form only for 2012, i.e., not before the start of our sample period. We therefore do not use it for our baseline estimations.
[21] Another important determinant of default, following conversation with practitioners, is divorce, but divorces are so far not known to exhibit any systemic cyclical patterns in Switzerland.

These tell us that a bank would be up to 32% more likely to extend an offer, and give a discount of up to 33 bps when unemployment rates as drivers of default probabilities are perfectly negatively correlated between the borrower's and the lender's own canton. More realistically, offer propensities are implied to be up to 2.24% higher and prices up to 2.3 bps lower when the unemployment rate correlation is 1 standard deviation or 0.07 units lower.

*Robustness*

In the Online Appendix, Table AT8 replaces the complementarity measure based on unemployment rates with a measure based on house price growth, based on the consideration that larger house price decreases in crises imply higher loss given default (LGD). Here we find that a change in complementarity by one standard deviation or 0.19 units increases the offer propensity by up to 1.14% and lowers the price by up to 1.14 bps. These responses are somewhat smaller than those to unemployment rate complementarity, which makes sense insofar as ideally the bank wants to keep the probabilities of default in its entire portfolio low. Use of remaining collateral values in a foreclosure procedure becomes necessary only conditional on default and in addition will at least imply additional costs even when the collateral value does still exceed the remaining debt.

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

Based on the branch location information, in Table AT9 we also asses how current branch presence matters for offering and pricing. We find that banks are less likely to offer to a canton where they have no branch presence yet, but if they do, they offer better prices. We find these findings broadly in line with aformentioned results on how banks respond to their prior mortgage portfolio.

Finally, Table AT10 in the Online Appendix combines our baseline analyses on banks' responses to market concentration from Table 2 with the baseline analyses on risk management incentives from Table 4. In contrast to Table 4 and in line with Table 2, columns 5 and 6 can control for household group fixed effects but cannot use fixed effects for every single household due to collinearity with the only inter-cantonal variation in HHI. This is one of the reasons why our baseline analyses investigate competition and risk management considerations separately. But overall Table A10 strongly confirms our findings on bank responses to both HHI and risk management considerations and hence shows that both findings exist on their own and neither is simply driven by the other. So we decided to treat the two topics separately in our baseline, allowing us to use for each the most conservative specification possible as well as to speak to several distinct strands of the literature.

### 5.3 Results on Automation

As per our *Hypotheses 3*, Table 5 follows largely the same outline as Table 2 in that columns 1, 3 and 5 focus on the offer and columns 2, 4 and 6 on the pricing decision. Also in line with Table 2, columns 1-2 use bank and household controls, 3-4 replace bank controls with bank fixed effects, and columns 5-6 also replace household controls with household group fixed effects. Like in Table 2, we use fixed effects for each household group defined by all characteristics except location so that we can still estimate the effect of local market concentration. Unlike in Table 2, we do not instrument market concentration here.

More importantly, the outcome for which we display coefficients here is not offer or pricing itself, but the log of the squared residual not explained by the estimated bank rules. Starting with household characteristics, we find that offer decisions have a 62-70% larger squared residual and hence a 7.9-8.3% larger residual, which we call discretion, when the LTV ratio exceeds 80%. Likewise, we observe 4.6-4.9% more discretion when the LTI ratio exceeds 4.5, and another 7.5-7.9% when it exceeds 5.5. In addition, pricing decisions contain 6.2-7.3% more discretion already when the LTV ratio exceeds two-thirds. These findings clearly support our *Hypothesis 3a* whereby decisions on riskier clients tend to be escalated to manual or even senior decisions. By contrast, decisions on safer clients are to a greater extent left to automated choice. This is consistent with the predictions in Petersen and Rajan (1995) whereby banks exert more discretion when lending to more “opaque” and hence harder-to-value firms.

Relatedly, we find 2.2-3.9% less discretion in decisions for each percent by which the bank has a larger balance sheet. We also find 1.4-1.7% less discretion for each percentage point of total assets previously invested in mortgages. These two findings confirm our *Hypothesis 3b* whereby banks with more prior mortgage expertise can automate their decision-making to a larger extent. Further, we find less discretion in decisions about applications from more concentrated and more complementary markets. These two findings are in line with those discussed above whereby banks are particularly eager to lend to those markets, and this preference may dominate other considerations sufficiently often that banks decide in a more automated fashion and hence more quickly in these cases.

Finally, we observe 1.4-2.8% less discretion in offer choices for each 1’000 responses made before. Interestingly we cannot confirm that this experience allows banks also to automate their pricing more, but we consider the greater automation of offer decisions as confirming *Hypothesis 3c* above. Table AT11 in the Online Appendix displays the underlying *mean equation* estimates. They correspond largely to those already discussed above with more and cheaper offers for safer clients, as well as from larger or more mortgage-focused banks, to more concentrated markets, and to markets more complementary to banks’ existing portfolios. They also suggest that offer propensity increases in bank experience, although only by 1% per 1’000 previous responses and the effect on pricing is not robust across specifications.

Increasing automation can allow banks to cut operational costs. Admittedly we cannot explicitly observe whether greater automation comes at the cost of more wrong decisions. But the fact that in the setup studied banks dispose of high-quality hard but no soft information suggests to us that decision quality would be unlikely to better if decisions were made with more discretion.

## 6 Conclusion

In this paper we have investigated how mortgage lending changes through a FinTech 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. 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. We obtain three key findings.

First, we observe that when responding to an application from a market with a HHI of 0.25, above which the US DoJ would call it highly concentrated, a bank is up to 3.5% more likely to make an offer and in addition is willing to lower its price by up to 6.7 bps, relative to a market with a HHI of 0.15, below which the US DoJ considers markets to have a low market concentration. This finding may be counter-intuitive prima facie, where one may have expected that higher concentration allows banks to the opposite to make *less* attractive offers. But more concentrated markets also offer online bidders the chance to get "a foot in the door" in markets with in expectation more attractive future business. For potential borrowers located in such hitherto more concentrated markets, this implies that the availability of an online platform can lead to more and better mortgage offers.

We have obtained these findings by instrumenting actual cantonal market concentration with concentrations predicted from the need of the Swiss big two banks to cut their domestic mortgage lending following losses in the US. While the exploitation of pre-existing variation in exposure to exogenous supply shifts has recently been exploited by a number of papers, it is particularly clean in our setup of interest, as the US crisis struck virtually all global banks with US presence and is arguably quite exogenous to later Swiss online mortgage bidding of small local banks with no US subprime exposure.

Second, banks offer about 2% (1%) more often and in addition reduce their prices by about 2 bps (1bps) more if the applicant's state has a one standard deviation lower unemployment rate (house price change) correlation with the bank's own state. So the platform allows banks to improve the inter-regional allocation of their mortgage portfolio and hence ceteris paribus improve their risk management following amongst others Quigley and Van Order (1991). We deem the risk management benefits from more inter-regional diversification to dominate potential increases in the cost of raising information on more regions, as validly raised by Loutskina and Strahan (2011), in the market analyzed. For collateral values here are assessed with the same hedonic models country-wide and information on borrowers are equally reliable 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, in our Online Appendix we investigate in addition 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. We also find that the degree of automation thus measured increases the more online responses the bank has already sent out. This suggests that longer participation can help banks reduce operational costs. Absent a crisis we do not yet know for sure whether such automation increases the potential for erroneous decisions in the sense of under- (or over-) pricing credit risk. We do however observe banks to price in all commonly considered mortgage risk factors such as LTV and LTI ratios, , 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, and by exploiting quasi-experimental variation in market concentration.

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## Table 1: Descriptive Statistics

| | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **(A) Applicant Characteristics** | | | | | |
| Year | 25'125 | 2011 | 1 | 2010 | 2013 |
| Month | 25'125 | 6 | 3 | 1 | 12 |
| Mortgage Amount in CHF | 25'125 | 566'274 | 332'695 | 100'000 | 2'000'000 |
| I(New Mortg.=1) | 25'125 | 0.54 | 0.5 | 0 | 1 |
| Loan-to-Value (LTV) | 25'125 | 64.5 | 17.3 | 15 | 90 |
| I (LTV > 67%) | 25'125 | 0.53 | 0.5 | 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 |
| Household Total Income | 25'125 | 167'603 | 88'961 | 48'000 | 600'000 |
| Household Rental Income | 25'125 | 4'232 | 16'880 | 0 | 116'000 |
| Household Other Income | 25'125 | 9'381 | 28'329 | 0 | 200'000 |
| Household Wealth incl. Pension Fund | 25'125 | 469'333 | 515'877 | 10'000 | 3'180'000 |
| Applicant Age | 25'125 | 46 | 10 | 28 | 73 |
| I(Applicant Age>=38) | 25'125 | 0.22 | 0.41 | 0 | 1 |
| **(B) Regional Characteristics** | | | | | |
| Herfindahl-Hirschmann Index (HHI) | 25'125 | 0.18 | 0.05 | 0.12 | 0.49 |
| Multi-Market Contact (MMC) Index | 25'125 | 0.07 | 0.03 | 0.05 | 0.4 |
| Cantonal Share of Foreigners in 2010 | 25'125 | 20.8 | 5.3 | 9.74 | 39.11 |
| Number of Online Providers (NOP) | 25'125 | 10.92 | 2.52 | 4 | 14 |
| Single-Family Home Price Growth | 25'125 | 4.07 | 4.07 | -3.99 | 15.27 |
| **(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 | 47.8 | 17.9 | 16.72 | 65.63 |
| Capital Ratio | 25'125 | 7.25 | 1.03 | 4.72 | 11.33 |
| Experience in 1'000 Web Responses | 25'125 | 4.07 | 2.94 | 0.00 | 10.15 |
| **(D) Interaction Characteristics** | | | | | |
| Correlation of Unempl. Rates 1973-2019 | 25'125 | 0.92 | 0.07 | 0.68 | 1 |
| House price growth correlation | 25'125 | 0.77 | 0.19 | 0.15 | 1 |
| Responses per Application | 25'125 | 4.24 | 1.45 | 1 | 10 |
| Response Time in Hours | 25'125 | 97.41 | 151.72 | -2.73 | 789.1 |
| I (Offer = 1) | 25'125 | 0.82 | 0.38 | 0 | 1 |
| Weighted Rate Offered | 20'583 | 2.16 | 0.56 | 0.93 | 3.25 |
| Weighted Spread Offered | 20'583 | 0.9 | 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. (D) shows key response characteristics, including the number of responses the bank has already sent out. Unemployment and house price change correlation measure the correlation between the applicant's and the bank's canton. Weighted Spread is the amount-weighted average across the 1-3 tranches offered, where spread is the rate offered less the swap rate for the corresponding maturity.

## Table 2: Entering Concentrated Markets

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| HHI | 0.78*** | -0.54*** | 1.20*** | -0.57*** | 1.51*** | -0.50*** |
| | (0.29) | (0.04) | (0.31) | (0.04) | (0.44) | (0.04) |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.10*** | 0.02*** | 0.10*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -1.40* | 0.09 | -0.92 | -0.05 | | |
| | (0.77) | (0.10) | (0.80) | (0.09) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.02*** | -0.01*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.06*** | -0.05*** | | | | |
| | (0.01) | (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 | -0.46* | 1.67*** | 0.67** | 1.20*** | | 1.02*** |
| | (0.27) | (0.05) | (0.27) | (0.03) | | (0.02) |
| d(Offer)/d(HHI) | 0.18*** | | 0.28*** | | 0.35*** | |
| | (0.07) | | (0.07) | | (0.10) | |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 24,428 | 20,583 |
| Estimation | IV Probit | IV Probit | IV Probit | IV | 2SRI Logit | IV |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

HHI is the Herfindahl-Hirschmann Index (HHI), i.e. the sum of squared market shares, in cantonal mortgage markets in the year of the bank response. It is instrumented with its prediction, obtained as the HHI level in 2009 plus the predicted change. The predicted change is the Switzerland-wide change between 2009 and the year of the bank response, times the cantonal market share of the "Big Two" banks UBS and CS in 2009. That market share is measured in terms of mortgage volumes. Household controls include indicators for loan-to-value (LTV) ratios above 2/3 and above 80%, for Loan-to-Income (LTI) ratios above 4.5 and above 5.5, and for a new rather than refinancing mortgage application, as well as cantonal house price growth and the number of other banks also offering online to that canton. Bank controls include the log of the responding bank's total assets and the shares in total assets of respectively mortgages, deposits, and equity. Columns with unequal numbers analyze banks' response to HHI in terms of offer propensities using (IV) Probit regressions (except for Column 5 due to the incidental parameter problem, see text), Columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1-2 use both household and bank controls, 3-4 replace bank controls with bank fixed effects, while 5-6 also replace household controls with fixed effects for household groups constructed from the LTV range, the LTI range, the refinancing indicator, a year dummy and a month dummy. See text for the rationale. Column 5 combines logit with 2-stage residual inclusion (2SRI), see Section 4.3 for details. Unless indicated otherwise, standard errors in parentheses are clustered by household group. * $p<0.1$, ** $p < 0.05$, *** $p<0.01$.

## Table 3: For which Households Are Responses to Local Market Concentration Strongest

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Offer | Price | Offer | Price | Offer | Price |
| HHI | 0.71 | -0.36*** | 1.60 | -0.36*** | 2.17* | -0.42*** |
| | (0.63) | (0.09) | (0.00) | (0.09) | (1.27) | (0.08) |
| HHI*I(Age < 38) | 0.60 | -0.18* | 0.13 | -0.19** | 1.31 | -0.18* |
| | (0.67) | (0.10) | (0.00) | (0.10) | (1.05) | (0.10) |
| HHI*I(New) | -0.07 | -0.23*** | -0.14 | -0.24*** | -0.61 | -0.16* |
| | (0.57) | (0.09) | (0.00) | (0.08) | (0.90) | (0.09) |
| HHI*(Foreign Share) | -0.00 | -0.00 | -0.03 | -0.00 | 0.00 | -0.00 |
| | (0.03) | (0.00) | (0.00) | (0.00) | (0.06) | (0.00) |
| HHI*I(Amount ≥ 1 mio) | -0.65 | -0.17 | -0.88 | -0.24* | -2.71 | -0.17 |
| | (0.95) | (0.13) | (0.00) | (0.13) | (1.74) | (0.13) |
| I(LTV>=67%) | -0.04 | 0.05*** | -0.06 | 0.05*** | | |
| | (0.03) | (0.00) | (0.00) | (0.00) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.78 | 0.03*** | | |
| | (0.05) | (0.01) | (550.85) | (0.01) | | |
| I(LTI>=4.5) | -0.17*** | 0.00 | -0.14 | 0.00 | | |
| | (0.03) | (0.00) | (150.80) | (0.00) | | |
| I(LTI>=5.5) | -0.84*** | 0.03*** | -0.78 | 0.03*** | | |
| | (0.05) | (0.01) | (0.00) | (0.01) | | |
| I(New Mortg.=1) | 0.12 | 0.07*** | 0.12 | 0.07*** | | |
| | (0.11) | (0.02) | (0.00) | (0.02) | | |
| I(Age < 38) | -0.13 | 0.04** | -0.03 | 0.04** | | |
| | (0.13) | (0.02) | (261.21) | (0.02) | | |
| (Foreign Share) | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | -0.00 |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) |
| I(Amount ≥ 1 mio) | -0.01 | 0.03 | 0.07 | 0.04 | 0.30 | 0.02 |
| | (0.19) | (0.03) | (0.00) | (0.03) | (0.34) | (0.03) |
| House price growth | -1.38* | 0.10 | -2.43 | -0.03 | | |
| | (0.78) | (0.10) | (0.00) | (0.09) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.01 | -0.01*** | 0.04*** | -0.01*** |
| | (0.01) | (0.00) | (0.00) | (1.12) | (0.01) | (0.00) |
| Ln(Total Assets) | 0.06*** | -0.05*** | | | | |
| | (0.01) | (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 | -0.52* | 1.64*** | 0.46 | 1.16*** | | 1.11*** |
| | (0.31) | (0.05) | (0.00) | (0.03) | | (0.02) |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 24,428 | 20,583 |
| Estimation | IV Probit | IV | IV Probit | IV | 2SRI Logit | IV |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| HH Group FE | No | No | No | No | Yes | Yes |

This table follows largely the same specification and methodology as Table 2, but adds interactions of the HHI measure with an indicator for applicants aged below 38, with an indicator for a new mortgage application rather than a refinancing application, with the share of foreigners resident in the applicant's canton in 2010, and with an indicator for amounts greater CHF 1 mio. It instruments these with their interactions with our instrument from Table 2. See notes of Table 2 for further details. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table 4: Risk Management through Unemployment Complementarity

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| Unemp. Complementarity | 1.36*** | -0.33*** | 0.64*** | -0.24*** | 2.41*** | -0.25*** |
| | (0.21) | (0.03) | (0.24) | (0.03) | (0.66) | (0.03) |
| HHI | 0.17 | -0.39*** | 0.49* | -0.43*** | | |
| | (0.26) | (0.03) | (0.27) | (0.03) | | |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.84*** | 0.02*** | -0.85*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | -0.00 | -0.17*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.86*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.09*** | 0.02*** | 0.09*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| Ln(Total Assets) | 0.03** | -0.04*** | | | | |
| | (0.01) | (0.00) | | | | |
| Mortgages/TA | 0.02*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Deposits/TA | -0.01*** | 0.00* | | | | |
| | (0.00) | (0.00) | | | | |
| Equity/TA | 0.07*** | 0.01*** | | | | |
| | (0.01) | (0.00) | | | | |
| Constant | 0.90*** | 1.31*** | 1.67*** | 0.85*** | | 0.72*** |
| | (0.29) | (0.05) | (0.35) | (0.04) | | (0.04) |
| d(Offer)/d(Compl.) | 0.32*** | | 0.15*** | | 0.10* | |
| | (0.05) | | (0.05) | | (0.05) | |
| Observations | 25,060 | 20,533 | 25,048 | 20,533 | 9,689 | 20,533 |
| Estimation | Probit | OLS | Probit | OLS | Logit | OLS |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH FE | No | No | No | No | Yes | Yes |

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

## Table 5: Automating Market Entry and Diversification around a Common Rule

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

Regressors and specifications follow those in Tables 2-4, but add "Experience" as the number of online mortgage applications (In 1'000) the responding bank has already processed since the platform start in 2008. In the Online Appendix we display the underlying *mean equation* relating offers and prices to these regressors. Here we display the *variance equation* relating the log of the squared residual from the mean equation to the regressors of interest. Standard errors in parentheses are robust. * p<0.1, ** p < 0.05, *** p<0.01.

# Online Appendix

In this Online Appendix, Section A1 briefly discusses a number of robustness checks on our analyses on **market concentration**, A2 those on **risk management**, and A3 those on **automation**. Following these three sections, Section A4 investigates the extent to which borrowers and lenders on the platform we study are **representative** for the full national mortgage market. The corresponding tables follow the four sections.

## A1. Local Market Concentration

To start with, Table AT1 repeats our analyses on banks' responses to local competition, but to instrument cantonal mortgage market competition it maps the lending reduction of the Big Two into cantons based on the big two banks' prior market share measured in terms of deposit volumes rather than mortgage volumes. Relatedly, Table AT2 computes the mapping on the basis of the number of deposit accounts rather than deposit volumes. Apart from using a different instrument, both tables follow exactly the same structure as Table 2 in the paper in terms of both left- and right-hand side variables. The results of both checks can be summarized very briefly in that results are very similar in terms of sign, statistical significance and even size. This reflects that in Swiss domestic commercial banking market shares in deposit and mortgage markets tend to be linked very closely.

Following that, Table AT3 presents in columns 1-3 the first-stage regressions underlying Table 2, in columns 4-6 those underlying Table AT1, and in columns 7-9 those underlying Table AT2. The table shows that with all three instruments we obtain very strong first stage coefficients of interest, so that our analyses do not suffer from weak instruments.

Table AT4 repeats the analyses from Table 2 but uses Ordinary Least Squares instead of Instrumental Variable regressions, and complements the Herfindahl-Hirschmann Index (HHI) of cantonal market concentration with the Multi-Market Contact (MMC) measure of competition intensity as used also in Degryse and Ongena (2007). This follows the idea in Edwards (1955) of a "linked oligopoly" under which multi-market contact increases banks' incentives to collude and hence leads them to behave less competitively. On the other hand though, Park and Pennacchi (2009) 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 $MMC_j = \frac{2}{26 f_j (f_j - 1)} \sum_{k=1}^{180} \sum_{l=k+1}^{180} a_{kl} D_{kj} D_{lj}$.

The coefficients in columns 1-4 suggest that when the average bank active in the applicant's canton meets more of its competitors there also in other cantons, it is more likely to offer also here and at more competitive prices. This is more in line with the findings of Park and Pennacchi (2009), whereby multi-market contact promotes competitive behavior, than with the original "linked oligopoly" hypothesis of Edwards (1955) whereby it promotes collusion. We note however that in the setup studied multi-market competition loses its economic and statistical significance in columns 5-6 where we control for both bank and household group effect. We attribute this to the fact that the Swiss mortgage market is characterized by many small banks who often meet each other only in a very limited number of cantonal markets. This feature of many small hitherto rather local banks however is one that motivates also our second field of interest of how going online allows them to become less local with potential benefits for their portfolio diversification.

In addition, Table AT5 repeats our Bartik (1991) instrumental variable estimates of the effect of local market competition on pricing, but uses the methods recently proposed by Adão, Kolesár and Morales (2019) to compute standard errors for shift-share estimations. In particular, their methodology accounts for the fact that residuals between regions with similar Bartik shares, i.e., in our case between regions with similar pre-existing market shares of the Big Two, are likely to be correlated. Since their correction method is not currently available for non-linear estimation, we depart from our baseline by estimating also the regressions for the binary outcome offer in columns 1, 3 and 5 with a linear probability model rather than a probit model in the second stage. The resulting point estimates for the marginal effect on offer propensities with the three different sets of covariates are respectively 18, 27 and 18 percent compared to 18, 28 and 35 estimated with the probit methodology. More importantly for the purpose at hand, all relevant estimators remain statistically significant at the 1% level or below. This is true both when we use Adão, Kolesár and Morales (2019) 's default methodology "AKM" as well as their alternative "AKM0", which we do not display here for reasons of space.

Relatedly, Table AT6 repeats the same estimations but clusters standard errors by the 26 cantons rather than by the 708 household groups. Given the small number of clusters in this case, we follow Cameron, Gelbach and Miller (2008) and Roodman et al. (2019) in re-computing at the bottom of the table the p-values for the coefficients of interest on HHI also using wild bootstrapping. With and without bootstrapping, the coefficients remain statistically significant at least at the 5% level, except for that in Column 1, where the P value increases to 16%. As the specifications with fixed effects seem more credible to us anyway, we take this to confirm that our estimates of interest are robust to how we compute standard errors.

In addition, Table AT7 repeats the same estimations but uses a Herfindahl-Hirschmann Index (HHI) of market concentration which is based not on banks' shares in mortgage stocks on their balance sheets, but instead on their shares in all cantonal bank branches as observed in the 2012 phone book. A drawback of this measure is that we currently observe it in digital form only for 2012, i.e., not before the start of our sample period, and therefore we do not use it for our baseline estimations. However, the results confirm those in Table 2 and in some cases are even slightly larger, thus confirming that results do not hinge on a particular way of measuring market concentration.

### A2. Risk Management

Table AT5 replaces the complementarity measure based on unemployment rates with complementarity based on house price changes. Here the results of one standard deviation change in the complementarity measure go in the same direction and are equally statistically significant, but are smaller in magnitude. We take this to reflect that the collateral value comes into play only after borrowers' incomes become insufficient to keep servicing the mortgage.

Finally, Table AT6 combines our baseline analyses on banks' responses to market concentration from Table 2 with the baseline analyses on risk management incentives from Table 4. In contrast to Table 4 and in line with Table 2, columns 5 and 6 can control for household group fixed effects but not use fixed effects for every single household due to collinearity with the only inter-cantonal variation in HHI. Overall the table strongly confirms our findings on bank responses to both HHI and risk management considerations. The average marginal effect of HHI on offer propensities in column (3, 5) shrinks slightly from 0.18 to 0.15 (0.28 to 0.24; 0.35 to 0.22), but remains economically and statistically significant. The effect of unemployment complementarity in column 1 (3, 5) remains unchanged at 0.32 (0.15, 0.15). Overall. this confirms that both dimensions are relevant on their own, in line with the fact that across all responses banks submit the correlation of our HHI measure of market concentration with unemployment complementarity is only 15%. Likewise, that with house price change complementarity is only 19%. Nonetheless, we decided to discuss competition and risk management separately above to give both sufficient attention and as they are linked to different strands of the literature.

### A3. Automation

Table AT7 presents the mean equation estimates underlying the variance equation estimates displayed in Table 5. Maybe the most interesting finding is that our pricing equations achieve R2 values of 29%

even with only a limited number of household and bank controls, 31% when we replace bank controls with bank fixed effects, and 34% when we additionally replace household controls with household group fixed effects. This is significantly higher than e.g. the 18% in Petersen and Rajan (2002) or even than the 22% in Degryse and Ongena (2005). We attribute this not to the sophistication of our model, but rather to the fact that in the setup studied banks disposed of reliable hard, but no soft information, favoring more rule-based decision-making. How they decide in response to household and bank characteristics, market concentration or portfolio complementarity corresponds to what we have already discussed in the main paper, but the one additional finding worth mentioning here is that offer probability is found to increase by 1% with each 1'000 responses already sent out. By contrast, the effect of experience on pricing is not robust across specifications.

### A4. Sample Representativeness

An important question when analyzing data from online lending is how representative these are of the offline market. To start with, Table AT12 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,[1] 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 the four language regions.

Likewise, Table AT13 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 heterogeneity of Switzerland in terms of language, religion, topography and urbanization, we argue that despite the limited size of the country, behavior is also representative of that in larger countries.

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

Finally, Table AT14 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 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 16% of mortgages start with an LTV value above 80%. But note that, as discussed in more detail in Basten (2020), these SNB values are based on asking each of the twenty-five largest mortgage lenders for the 50th, 75th, 90th, and 95th percentiles of their LTV distribution and then inferring from this which fraction of its mortgages had LTV ratios >80%. As this does not allow a sharp distinction between LTV≥80 and LTV>80, while our sample has a bunching of applications at LTV values of 79% and 80%, we report both the fraction of observations with LTV > 80, which is 8%, and the fraction with LTV>=80%, which is 23%. The value of 16% reported for the SNB sample is hence in between our two values, so that we cannot reject the null of no significant difference between the samples. 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. Unfortunately we cannot formally compare the two percentages with a t-test for lack of data on standard deviations in the SNB data. However, 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 platform or expanding their offline branch network, while the platform is particularly attractive for smaller banks.

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## Table AT1: Competition with Instrument Based on Deposit Volumes

| | (1)<br>Offer | (2)<br>Price | (3)<br>Offer | (4)<br>Price | (5)<br>Offer | (6)<br>Price |
|---|---|---|---|---|---|---|
| HHI | 0.81*** | -0.53*** | 1.21*** | -0.56*** | 1.34*** | -0.48*** |
| | (0.29) | (0.04) | (0.31) | (0.04) | (0.43) | (0.04) |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.10*** | 0.02*** | 0.10*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -1.42* | 0.08 | -0.93 | -0.06 | | |
| | (0.77) | (0.10) | (0.80) | (0.09) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.02*** | -0.01*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.06*** | -0.05*** | | | | |
| | (0.01) | (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 | -0.46* | 1.67*** | 0.67** | 1.20*** | 1.18*** | 1.02*** |
| | (0.27) | (0.05) | (0.27) | (0.03) | (0.36) | (0.02) |
| d(Offer)/d(HHI) | 0.19*** | | 0.28*** | | 0.21*** | |
| | (0.07) | | (0.07) | | -0.07 | |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 25,113 | 20,583 |
| Estimation | IV Probit | IV | IV Probit | IV | 2SRI Logit | IV |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

HHI is the Herfindahl -Hirschmann Index (HHI), i.e. the sum of squared market shares, in cantonal mortgage markets in the year of the bank response. It is instrumented with its prediction, obtained as the HHI level in 2009 plus the predicted change. The latter is obtained as Switzerland-wide change between 2009 and the year of the bank response times the cantonal market share of the "Big Two" banks UBS and CS in 2009. In contrast to Table 2 and 3, market share is now measured in terms of deposit volumes. Household and bank controls as in Table 2. Columns with unequal numbers analyze banks' response to HHI in terms of offer propensities using (IV) Probit regressions (except for Column 5 due to the incidental parameter problem, see text), Columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1-2 use both household and bank controls, 3-4 replace bank controls with bank fixed effects, while 5-6 also replace household controls with fixed effects for household groups constructed from the LTV range, the LTI range, the refinancing indicator, a year dummy and a month dummy. Column 5 combines logit with 2-stage residual inclusion (2SRI), see Section 4 for details. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT2: Competition with Instrument Based on Deposit Accounts

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| HHI | 0.80*** | -0.52*** | 1.18*** | -0.55*** | 1.44*** | -0.48*** |
| | (0.29) | (0.04) | (0.31) | (0.04) | (0.45) | (0.04) |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.10*** | 0.02*** | 0.10*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -1.42* | 0.07 | -0.91 | -0.06 | | |
| | (0.77) | (0.10) | (0.80) | (0.09) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.02*** | -0.01*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.06*** | -0.05*** | | | | |
| | (0.01) | (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 | -0.46* | 1.67*** | 0.67** | 1.19*** | | 1.02*** |
| | (0.27) | (0.05) | (0.27) | (0.03) | | (0.02) |
| d(Offer)/d(HHI) | 0.19*** | | 0.27*** | | 0.34*** | |
| | (0.07) | | (0.07) | | (0.11) | |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 24,428 | 20,583 |
| Estimation | IV Probit | IV | IV Probit | IV | 2SRI Logit | IV |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

HHI is the Herfindahl -Hirschmann Index (HHI), i.e. the sum of squared market shares, in cantonal mortgage markets in the year of the bank response. It is instrumented with its prediction, obtained as the HHI level in 2009 plus the predicted change. The latter is obtained as Switzerland-wide change between 2009 and the year of the bank response times the cantonal market share of the "Big Two" banks UBS and CS in 2009. In contrast to Table 2 and 3, market share is now measured in terms of the number of deposit accounts. Household and bank controls as in Table 2. Columns with unequal numbers analyze banks' response to HHI in terms of offer propensities using (IV) Probit regressions (except for Column 5 due to the incidental parameter problem, see text), Columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1-2 use both household and bank controls, 3-4 replace bank controls with bank fixed effects, while 5-6 also replace household controls with fixed effects for household groups constructed from the LTV range, the LTI range, the refinancing indicator, a year dummy and a month dummy. Column 5 combines logit with 2-stage residual inclusion (2SRI), see Section 4 for details. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT3: First Stage Regressions for Competition Analyses

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | HHI | HHI | HHI | HHI | HHI | HHI | HHI | HHI | HHI |
| Mortg. Vol. Share | 0.94*** | 0.94*** | 0.96*** | | | | | | |
| | (0.00) | (0.00) | (0.00) | | | | | | |
| Dep. Vol. Share | | | | 0.96*** | 0.95*** | 0.96*** | | | |
| | | | | (0.00) | (0.00) | (0.00) | | | |
| Dep. No. | | | | | | | 0.96*** | 0.96*** | 0.97*** |
| | | | | | | | (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) | | (0.00) | (0.00) | | (0.00) | (0.00) | |
| I(LTV>=80%) | -0.00 | -0.00 | | -0.00 | -0.00 | | -0.00 | -0.00 | |
| | (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** | |
| | (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 | |
| | (0.00) | (0.00) | | (0.00) | (0.00) | | (0.00) | (0.00) | |
| I(New Mortg.=1) | 0.00* | 0.00 | | 0.00 | 0.00 | | 0.00 | 0.00 | |
| | (0.00) | (0.00) | | (0.00) | (0.00) | | (0.00) | (0.00) | |
| House price growth | 0.18*** | 0.17*** | | 0.23*** | 0.22*** | | 0.27*** | 0.26*** | |
| | (0.01) | (0.01) | | (0.02) | (0.02) | | (0.02) | (0.02) | |
| Number of Web Providers | 0.00 | 0.00 | | 0.00*** | 0.00*** | | 0.00*** | 0.00*** | |
| | (0.00) | (0.00) | | (0.00) | (0.00) | | (0.00) | (0.00) | |
| Ln(Total Assets) | 0.00*** | | | 0.00*** | | | 0.00*** | | |
| | (0.00) | | | (0.00) | | | (0.00) | | |
| Mortgages/TA | 0.00*** | | | 0.00*** | | | 0.00*** | | |
| | (0.00) | | | (0.00) | | | (0.00) | | |
| Deposits/TA | -0.00* | | | -0.00 | | | -0.00*** | | |
| | (0.00) | | | (0.00) | | | (0.00) | | |
| Equity/TA | 0.00 | | | -0.00*** | | | -0.00*** | | |
| | (0.00) | | | (0.00) | | | (0.00) | | |
| Constant | 0.03*** | 0.03*** | 0.02*** | 0.02*** | 0.02*** | 0.02*** | 0.02*** | 0.02*** | 0.02*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Observations | 25,125 | 25,125 | 25,125 | 25,125 | 25,125 | 25,125 | 25,125 | 25,125 | 25,125 |
| R2 | 0.97 | 0.98 | 0.97 | 0.96 | 0.96 | 0.95 | 0.96 | 0.96 | 0.95 |

This table shows in Columns 1-3 the first-stage (FS) regressions underlying our IV regressions in Table 2, in Columns 4-6 those underlying Table A1, and in Columns 7-9 those underlying Table A2. In each of these, the first column always shows the version with both household and bank controls, the second shows that with household controls and bank fixed effects, and the third shows that with household group fixed effects and bank fixed effects. All controls are the same as in the respective second-stage IV regressions. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT4: Competition without Instrument, with Multi-Market Contact (MMC)

| | (1)<br>Offer | (2)<br>Price | (3)<br>Offer | (4)<br>Price | (5)<br>Offer | (6)<br>Price |
|---|---|---|---|---|---|---|
| HHI | 0.55 | -0.34*** | 0.60* | -0.44*** | 1.17** | -0.49*** |
| | (0.33) | (0.04) | (0.35) | (0.04) | (0.48) | (0.04) |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.86*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.10*** | 0.02*** | 0.10*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -1.09 | -0.17* | -0.26 | -0.20** | | |
| | (0.82) | (0.09) | (0.85) | (0.09) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.03*** | -0.01*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Multi-Market Competition | 0.75 | -0.61*** | 1.80*** | -0.39*** | 0.16 | 0.07 |
| | (0.55) | (0.07) | (0.61) | (0.08) | (0.78) | (0.06) |
| Ln(Total Assets) | 0.06*** | -0.05*** | | | | |
| | (0.01) | (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 | -0.56* | 1.75*** | 0.47* | 1.24*** | | 1.01*** |
| | (0.29) | (0.05) | (0.28) | (0.03) | | (0.02) |
| d(Offer)/d(HHI) | 0.13 | | 0.14* | | 0.28** | |
| | (0.08) | | (0.08) | | (0.11) | |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 24,428 | 20,583 |
| Estimation | Probit | OLS | Probit | OLS | Logit | OLS |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

Variables correspond to those in Table 2, but here the HHI is not instrumented. Furthermore, we additionally include here the Multi-Market Contact (MMC) measure, as explained in the text. Columns 1, 3 and 5 analyze the response in terms of offer propensities, while columns with equal numbers analyze the response in terms of the spread above maturity-congruent interest rate swap rates. Columns 1-2 use both household and bank controls, 3-4 replace bank controls with bank fixed effects, while 5-6 also replace household controls with fixed effects for household groups constructed from the LTV range, the LTI range, the refinancing indicator, a year dummy and a month dummy. See text for the rationale. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT5: Effects of Competition with AKM Standard Errors

| | (1)<br>Offer | (2)<br>Price | (3)<br>Offer | (4)<br>Price | (5)<br>Offer | (6)<br>Price |
|---|---|---|---|---|---|---|
| HHI | 0.18*** | -0.54*** | 0.27*** | -0.57*** | 0.18*** | -0.50*** |
| | (0.05) | (0.03) | (0.06) | (0.03) | (0.05) | (0.03) |
| I(LTV>=67%) | -0.01** | 0.05*** | -0.01** | 0.05*** | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | |
| I(LTV>=80%) | -0.27*** | 0.03*** | -0.27*** | 0.03*** | | |
| | (0.01) | (0.01) | (0.01) | (0.01) | | |
| I(LTI>=4.5) | -0.04*** | 0.00 | -0.04*** | 0.00 | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| I(LTI>=5.5) | -0.28*** | 0.03*** | -0.28*** | 0.03*** | | |
| | (0.01) | (0.01) | (0.01) | (0.01) | | |
| I(New Mortg.=1) | 0.02*** | 0.02*** | 0.02*** | 0.02*** | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | |
| House price growth | -0.37** | 0.09 | -0.27* | -0.05 | | |
| | (0.15) | (0.08) | (0.15) | (0.08) | | |
| Number of Web Providers | 0.00*** | -0.01*** | 0.01*** | -0.01*** | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | |
| Ln(Total Assets) | 0.01*** | -0.05*** | | | | |
| | (0.00) | (0.00) | | | | |
| Mortgages/TA | 0.00*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Deposits/TA | -0.00*** | 0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Equity/TA | 0.01*** | 0.02*** | | | | |
| | (0.00) | (0.00) | | | | |
| Constant | 0.51*** | 1.67*** | 0.77*** | 1.20*** | 0.01 | 0.74*** |
| | (0.05) | (0.03) | (0.06) | (0.02) | (0.06) | (0.05) |
| Observations | 25,125 | 20,583 | 25,125 | 20,583 | 25,125 | 20,583 |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| HH Group FE | No | No | No | No | Yes | Yes |
| Number of HH Groups | 654 | 654 | 654 | 654 | 654 | 654 |

All standard errors are computed using the AKM inference procedure described in Adao et al (2019). Results with the alternative "AKM0" procedure also described there are qualitatively the same. Because the procedure is currently available for linear second stages only, we estimate regressions for the binary outcome offer also with a linear probability model, rather than with a probit model as in our baseline. The resulting standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT6: Effects of Competition on Pricing, Clustering SEs by Canton

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| HHI | 0.78** | -0.54*** | 1.20*** | -0.57*** | 1.50*** | -0.50*** |
| | (0.39) | (0.12) | (0.41) | (0.12) | (0.44) | (0.04) |
| I(LTV>=67%) | -0.05 | 0.05*** | -0.05 | 0.05*** | | |
| | (0.03) | (0.01) | (0.03) | (0.01) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.04) | (0.01) | (0.04) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.01) | (0.03) | (0.01) | | |
| I(LTI>=5.5) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.04) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.10*** | 0.02*** | 0.10*** | 0.02*** | | |
| | (0.02) | (0.01) | (0.02) | (0.01) | | |
| House price growth | -1.40 | 0.09 | -0.92 | -0.05 | | |
| | (1.06) | (0.21) | (1.34) | (0.16) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.02*** | -0.01*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.06** | -0.05*** | | | | |
| | (0.03) | (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** | | | | |
| | (0.04) | (0.01) | | | | |
| Constant | -0.46 | 1.67*** | 0.67*** | 1.20*** | | 1.02*** |
| | (0.65) | (0.11) | (0.17) | (0.03) | | (0.02) |
| Bootstrapped P | 0.16 | 0.00 | 0.05 | 0.00 | 0.00 | 0.00 |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 24,428 | 20,583 |
| Estimation | IV Probit | IV | IV Probit | IV | 2SRI Logit | IV |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

The table repeats the estimations from Table 2 of the main paper, but now clusters standard errors by the 26 cantons rather than by household groups, except for columns 5 and 6 where the panel variable household group would not be nested within cantonal clusters and using canton as panel variable would take away all cross-sectional variation in the shift-share instrument. Given the small number of clusters, we display at the bottom alternative P-values for the coefficient on HHI based on bootstrapping with 100 iterations each, following Cameron, Gelbach and Miller (2008) and Roodman et al. (2019). Standard errors in parentheses are clustered by canton. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT7: Competition Results with Branch-Based HHI Measure

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| HHI | 1.19* | -0.93*** | 1.57** | -0.89*** | 0.99* | -0.67*** |
| | (0.68) | (0.12) | (0.64) | (0.12) | (0.55) | (0.08) |
| I(LTV>=67%) | -0.04 | 0.06*** | -0.04 | 0.06*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.86*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.16*** | -0.01 | -0.16*** | -0.00 | | |
| | (0.03) | (0.01) | (0.03) | (0.01) | | |
| I(LTI>=5.5) | -0.91*** | 0.04*** | -0.91*** | 0.03*** | | |
| | (0.06) | (0.01) | (0.06) | (0.01) | | |
| I(New Mortg.=1) | 0.12*** | 0.02*** | 0.12*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -0.09 | -0.76*** | 0.82 | -0.86*** | | |
| | (0.81) | (0.14) | (0.85) | (0.14) | | |
| Number of Web Providers | 0.05*** | -0.02*** | 0.05*** | -0.02*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.06*** | -0.05*** | | | | |
| | (0.01) | (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 | -0.94*** | 1.98*** | 0.06 | 1.47*** | | 1.09*** |
| | (0.36) | (0.06) | (0.34) | (0.05) | | (0.03) |
| d(Offer)/d(HHI) | 0.28* | | 0.36** | | 0.23* | |
| | (0.16) | | (0.15) | | (0.13) | |
| Observations | 25,550 | 20,828 | 25,538 | 20,828 | 24,853 | 20,828 |
| Estimation | IV Probit | IV | IV Probit | IV | 2SRI Logit | IV |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

The table analyses how banks' offer propensity and pricing vary between cantons (states) in which (observed only in 2012) the bank already has at least one branch and those where it does not. Note this is purely descriptive, as branch locations are of course also a choice variable. To account for canton size, all columns include canton fixed effects, in addition to the other sets of fixed effects (FE) as indicated above. Standard errors in parentheses are clustered by household. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT8: Risk Management through House Price Change Complementarity

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| House price change complementarity | 0.24*** | -0.03*** | 0.05 | -0.05*** | -0.05 | -0.06*** |
| | (0.07) | (0.01) | (0.09) | (0.01) | (0.26) | (0.01) |
| HHI | 0.20 | -0.40*** | 0.59** | -0.42*** | | |
| | (0.25) | (0.03) | (0.27) | (0.03) | | |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.84*** | 0.02*** | -0.85*** | 0.03*** | | |
| | (0.04) | (0.01) | (0.04) | (0.01) | | |
| I(LTI>=4.5) | -0.17*** | -0.00 | -0.17*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.86*** | 0.03*** | -0.87*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.09*** | 0.02*** | 0.09*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| Ln(Total Assets) | 0.03** | -0.04*** | | | | |
| | (0.01) | (0.00) | | | | |
| Mortgages/TA | 0.01*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Deposits/TA | -0.01*** | 0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Equity/TA | 0.05*** | 0.01*** | | | | |
| | (0.01) | (0.00) | | | | |
| Constant | 0.02 | 1.54*** | 1.05*** | 1.04*** | | 0.90*** |
| | (0.24) | (0.03) | (0.26) | (0.03) | | (0.02) |
| d(Offer)/d(Compl) | 0.06*** | | 0.01 | | -0.01 | |
| | (0.02) | | (0.02) | | (0.05) | |
| Observations | 25,125 | 20,583 | 25,113 | 20,583 | 9,759 | 20,583 |
| Estimation | Probit | OLS | Probit | OLS | Logit | OLS |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH FE | No | No | No | No | Yes | Yes |

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

## Table AT9: Responding to Cantons Where the Bank Has No Branches

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| I(No branches) | -0.20*** | 0.00 | -0.24*** | -0.03*** | -0.62*** | -0.03*** |
| | (0.03) | (0.00) | (0.04) | (0.00) | (0.08) | (0.00) |
| I(LTV>=67%) | -0.04 | 0.05*** | -0.04 | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.87*** | 0.03*** | -0.88*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.89*** | 0.03*** | -0.90*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.11*** | 0.02*** | 0.11*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -1.34 | -0.25** | -0.86 | -0.15 | | |
| | (1.00) | (0.11) | (1.01) | (0.11) | | |
| Number of Web Providers | -0.01 | 0.00 | 0.00 | -0.00 | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.02 | -0.05*** | | | | |
| | (0.02) | (0.00) | | | | |
| Mortgages/TA | 0.01*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Deposits/TA | -0.01*** | 0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Equity/TA | 0.03** | 0.01*** | | | | |
| | (0.01) | (0.00) | | | | |
| Constant | 0.86** | 1.48*** | 1.14*** | 1.07*** | | 0.96*** |
| | (0.35) | (0.06) | (0.33) | (0.05) | | (0.02) |
| Observations | 25,550 | 20,828 | 25,538 | 20,828 | 10,156 | 20,828 |
| d(Offer)/d(NoBranch) | -0.05*** | | -0.06*** | | -0.11*** | |
| | (0.01) | | (0.01) | | (0.03) | |
| Year*Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Canton FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Household FE | No | No | No | No | Yes | Yes |
| Estimation | Probit | OLS | Logit | OLS | Logit | OLS |

The table analyses how banks' offer propensity and pricing vary between cantons (states) in which (observed only in 2012) the bank already has at least one branch and those where it does not. Note this is purely descriptive, as branch locations are of course also a choice variable. To account for canton size, all columns include canton fixed effects, in addition to the other sets of fixed effects (FE) as indicated above. Standard errors in parentheses are clustered by the panel variable household. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT10: Competition and Risk Management Analyses Combined

| | (1) Offer | (2) Price | (3) Offer | (4) Price | (5) Offer | (6) Price |
|---|---|---|---|---|---|---|
| HHI | 0.62** | -0.51*** | 1.06*** | -0.54*** | 1.27*** | -0.46*** |
| | (0.29) | (0.04) | (0.31) | (0.04) | (0.46) | (0.04) |
| Unemp. Complementarity | 1.36*** | -0.32*** | 0.64*** | -0.23*** | 1.18*** | -0.24*** |
| | (0.21) | (0.03) | (0.23) | (0.03) | (0.44) | (0.03) |
| I(LTV>=67%) | -0.05* | 0.05*** | -0.05* | 0.05*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTV>=80%) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(LTI>=4.5) | -0.18*** | 0.00 | -0.18*** | 0.00 | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| I(LTI>=5.5) | -0.85*** | 0.03*** | -0.86*** | 0.03*** | | |
| | (0.05) | (0.01) | (0.05) | (0.01) | | |
| I(New Mortg.=1) | 0.10*** | 0.02*** | 0.10*** | 0.02*** | | |
| | (0.03) | (0.00) | (0.03) | (0.00) | | |
| House price growth | -1.44* | 0.08 | -0.98 | -0.03 | | |
| | (0.79) | (0.10) | (0.82) | (0.10) | | |
| Number of Web Providers | 0.02*** | -0.01*** | 0.02*** | -0.01*** | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| Ln(Total Assets) | 0.04*** | -0.04*** | | | | |
| | (0.01) | (0.00) | | | | |
| Mortgages/TA | 0.02*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Deposits/TA | -0.01*** | 0.00** | | | | |
| | (0.00) | (0.00) | | | | |
| Equity/TA | 0.07*** | 0.01*** | | | | |
| | (0.01) | (0.00) | | | | |
| Constant | 0.61* | 1.42*** | 1.36*** | 0.96*** | | 0.77*** |
| | (0.32) | (0.05) | (0.36) | (0.04) | | (0.04) |
| d(Offer)/d(HHI) | 0.15** | | 0.24*** | | 0.22** | |
| | (0.07) | | (0.07) | | (0.11) | |
| d(Offer)/d(Complement) | 0.32*** | | 0.15*** | | 0.20*** | |
| | (0.05) | | (0.05) | | (0.04) | |
| Observations | 25,060 | 20,533 | 25,048 | 25,060 | 24,326 | 20,533 |
| Estimation | IV Probit | IV | IV Probit | IV Probit | 2SRI Logit | IV |
| Bank FE | No | No | Yes | No | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH Group FE | No | No | No | No | Yes | Yes |

This table combines the analyses on the Herfindahl-Hirschmann Index (HHI) from Table 2, including the instrumentation strategy, with the Risk Management analyses on unemployment complementarity from Table 4. Following Table 2 and in deviation from Table 4, Columns 5 and 6 can control for household group fixed effects capturing all characteristics except for the place of residence, but cannot use fixed effects for each single household, as these would be fully collinear with the cantonal competition intensity HHI. For all other details, see the notes of Tables 2 and 4. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT11: Mean Equations Underlying the Variance Equations in Table 5

| | (1) Offer | (2) Spread | (3) Offer | (4) Spread | (5) Offer | (6) Spread |
|---|---|---|---|---|---|---|
| I(LTV>=67%) | -0.01** | 0.04*** | -0.01** | 0.02*** | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | |
| I(LTV>=80%) | -0.25*** | 0.02*** | -0.25*** | 0.02*** | | |
| | (0.01) | (0.01) | (0.01) | (0.01) | | |
| I(LTI>=4.5) | -0.04*** | 0.00 | -0.03*** | 0.00 | | |
| | (0.01) | (0.00) | (0.01) | (0.00) | | |
| I(LTI>=5.5) | -0.27*** | 0.03*** | -0.28*** | 0.03*** | | |
| | (0.01) | (0.01) | (0.01) | (0.01) | | |
| I(New Mortg.=1) | 0.03*** | 0.02*** | 0.03*** | 0.01*** | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | |
| Ln(Total Assets) | 0.01** | -0.04*** | | | | |
| | (0.00) | (0.00) | | | | |
| Mortgages/TA | 0.00*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Deposits/TA | -0.00*** | -0.00 | | | | |
| | (0.00) | (0.00) | | | | |
| Equity/TA | 0.02*** | 0.01*** | | | | |
| | (0.00) | (0.00) | | | | |
| HHI | 0.19*** | -0.34*** | 0.22*** | -0.24*** | 0.23*** | -0.34*** |
| | (0.05) | (0.03) | (0.05) | (0.03) | (0.06) | (0.04) |
| HP Growth | -0.27** | 0.04 | -0.06 | -0.12 | 0.06 | 0.02 |
| | (0.14) | (0.08) | (0.13) | (0.08) | (0.13) | (0.09) |
| Number Providers | 0.01*** | -0.01*** | 0.01*** | -0.01*** | 0.01*** | -0.01*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Unemp. Compl. | 0.21*** | -0.27*** | 0.13** | -0.17*** | 0.18*** | -0.14*** |
| | (0.05) | (0.03) | (0.05) | (0.03) | (0.05) | (0.03) |
| Experience | 0.01*** | 0.00*** | 0.01*** | 0.01*** | 0.01*** | -0.01*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | 0.59 | 1.23*** | 0.84*** | 0.88*** | 0.82*** | 0.91*** |
| | (0.00) | (0.04) | (0.08) | (0.03) | (0.00) | (0.00) |
| Observations | 25,060 | 20,533 | 25,060 | 20,533 | 25,060 | 20,533 |
| R2 | 0.11 | 0.29 | 0.13 | 0.31 | 0.19 | 0.34 |
| Bank FE | No | No | Yes | Yes | Yes | Yes |
| Year*Month FE | Yes | Yes | Yes | Yes | No | No |
| HH FE | No | No | No | No | Yes | Yes |

This table presents the Mean Equations underlying the Variance Equations displayed in Table 5 in the main paper. Experience is the number of online responses the bank has already sent out before, measured in units of 1'000. All other variables as in Tables 2-4. Standard errors in parentheses are clustered by household. * p<0.1, ** p < 0.05, *** p<0.01.

## Table AT12: Geographical Representativeness of Households

| Canton | (1) Number of Applications | (2) Percentage of Applications | (3) % of Mortgages Swiss Household Panel | (4) % of Volume All Swiss Banks |
|---|---|---|---|---|
| Aargau | 850 | 12.29 | 11.70 | 8.73 |
| Appenzell IR | 4 | 0.06 | 1.12 | 0.62 |
| Appenzell AR | 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 | 1.06 | 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 | 217 | 3.14 | 3.92 | 3.59 |
| Vaud | 607 | 8.78 | 7.28 | 8.07 |
| Zug | 118 | 1.71 | 0.56 | 2.04 |
| Zurich | 1'503 | 21.74 | 14.29 | 19.19 |
| Total | 6'914 | 100.00 | 100.00 | 100.00 |

The distribution in our sample counts each of the 6’914 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, significantly biased towards more urban areas.

## Table AT13: 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 AT14: Non-Geographical Representativeness

**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) | 0.08 | 0.16 | -0.09 |
| | (0.26) | (--) | (--) |
| Loan-to-Value (LTV) ratio >= 80% (0/1) | 0.23 | 0.16 | +0.07 |
| | (0.42) | (--) | (--) |
| 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.