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Mortgage Lending through a FinTech Web Platform. The Roles of Competition, Diversification, and Automation.

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Mortgage Lending through a FinTech Web Platform. The Roles of Competition, Diversification, and Automation.

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Christoph Basten[1] and Steven Ongena[2]

How do banks offer mortgages through an online platform to areas where they lack branches? Unique data on responses from different banks to each applying household show first that banks offer 6 percentage points (pp) more often and 5 basis points (bps) cheaper when market concentration has exogenously increased one standard deviation (SD) more, seeking follow-up profits. Second, they offer 2pp more often and 2bps cheaper when unemployment or house price growth in the applicant's state are 1SD less correlated with those in the bank's state, improving diversification. Third, automation to safer applicants by more experienced banks reduces operating costs.

Keywords: Mortgage Lending, Spatial Competition, Credit Risk, Automation, FinTech, Online Pricing, Bartik instrument, Pandemic

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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, 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 to the financial sector an emerging literature on how the internet changes competition pioneered by, amongst others, Cavallo (2017) and Gorodnichenko, Sheremirov, and Talavera (2018). 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 the option of online lending frees banks from brick and mortar legacies, 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] [2]

We exploit data from a Swiss online platform, 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

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[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.

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

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, 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 more local and from more 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. by Jiménez et al. (2012) or 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 and Sette (2016) who sent randomized simulated mortgage applications to different banks.[3]

To identify the causal effect of each canton'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 cantonal 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 Mian and Sufi (2012), Chodorow-Reich (2014) or Gete and Reher (2018), is particularly clean in our setup as US

[3] More recently, Chava 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.

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 Big Two 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 Bartik (1991) instruments, as recently discussed by Borusyak, Hull, and Jaravel (2018) and Goldsmith-Pinkham, Sorkin, and Swift (2020).[4] 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 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 or more competitive markets. However, offering lower prices instead to more concentrated markets allows banks to enter new, more profitable markets given customer switching costs.[5] Households thus obtain better offers.

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 probabilities of default (PD) and past house price changes as drivers of loss given default (LGD) are less correlated with those in the bank's home canton.

The role of these risk management relevant factors survives also when we control for various measures of distance between potential borrower and lender. This suggests that behavior which can be interpreted as improving banks' portfolio diversification, is not just driven by banks' strife to earn bigger margins in return for offering borrowers a nearer branch to bank at as in the Degryse and Ongena (2005) analysis of Belgian corporate loan pricing. In fact, on top of the effects of PD and LGD complementarity between borrower and lender canton, we also do find banks to charge lower prices to more distant borrowers, but while those effects are statistically significant their size is relatively small when we control for portfolio

[4] 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).

[5] The idea is that households make the effort of comparing prices from different providers when taking out a mortgage because much is at stake and prices are easily comparable. By contrast, they do not re-optimize often for e.g. their payment account or credit card as less is at stake and they do not get a personalized offer. Then the best package will depend on how often and where they withdraw cash, in which currencies, etc, making it harder to compare costs across different providers.

complementarity in addition to using both borrower and lender fixed effects. We rationalize this by observing that the changes in lender technology already noted by Petersen and Rajan (2002) for corporate lending are likely to apply even more to online mortgage lending.

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), 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 reductions in banks' ability to monitor loans located at a larger distance. While their risk measures cover banks' entire balance sheets, including loans to firms and other assets, we focus on how banks can better diversify specifically their mortgage portfolios. Through an online platform like the one studied here, lending decisions for different regions can still be made by the same central decision-maker, removing the agency problems between bank headquarters and local credit officers traditionally associated with larger distance. The online platform analyzed may thus reduce agency costs even beyond the level analyzed by Berger and DeYoung (2006), who found reductions in distance-related agency costs within US bank holding companies through improvements in information processing and telecommunication.[6]

[6] 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 to create new borrower lender matchings.

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, pioneered by 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. (2020). We so bring together the literature on rules vs discretion in banking (e.g., Cerqueiro, Degryse, and Ongena, 2010) with the recent literature on how the internet changes price setting (Cavallo, 2017; Gorodnichenki, Sheremirov, and Talavera, 2018). The latter 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.

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".[7] Of the four uses of this technology listed by Thakor, our paper focuses 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

[7] 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".

bank and yet have much the same effects.[8] 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.[9]

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 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-Klein model as summarized e.g. in Freixas and Rochet (2008) banks optimize lending and deposit business separately, then lend or borrow any difference between loan and deposit volumes in the interbank market. Further, they do so for a single period only. Then we expect banks to demand *higher* prices the *more* concentrated the market is.

But on the other hand, and potentially more realistically, clients in retail banking buy packages of services from the same bank including several components of mortgage loans, mortgage loan refinancing, deposit accounts, transaction accounts, or investment advice. This allows banks to cross-sell products. 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

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

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

paper on switching costs as one of two examples the effort required to close a transactions account with one bank, open one with another, and transfer all transactions information. Referring more specifically to lending, Sharpe (1990), Rajan (1992), and 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. Sharpe (1990) points out that such a setup "drives banks to lend to new firms at interest rates which initially generate expected losses", expecting later markup increases to make this worthwhile.[10]

More specifically in our setup households may deem it worthwhile to incur the search costs to find the cheapest mortgage, but are likely not to search anew for many follow-up businesses. One reason for this difference is that mortgage pre-payment is typically prohibitively expensive in Switzerland, so that mortgage borrowers are often stuck with their lender for 10 years or more. A second reason is that the attractiveness of different mortgage offers is easy to compare when everything bar the rate are standardized, whereas comparing, e.g., investment advice, brokerage fees, or account fees is harder. So 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 sees more profitable future business. So we posit:

<u>Hypothesis 1:</u> *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 Hypothesis on Risk Management

Petersen and Rajan (2002), Degryse and Ongena (2005) and Agarwal and Hauswald (2010) analyze how credit availability and pricing are related to borrower-lender distance, but they all focus on corporate lending. While Degryse and Ongena (2005) focus on banks' ability to charge

[10] In line with this Basten and Mariathasan (2020) 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 allowed banks to retain clients for future business.

a higher margin to nearby firms for sparing them commuting time, Agarwal and Hauswald (2010) add the role of distance for the collection of soft information and find closer firms to get more credit but at higher cost.[11] Petersen and Rajan (2002) find the role of distance for corporate lending to decrease due to advancements in technology. This selection of papers shows that distance per se is ambiguous as it may matter both for banks' ability to screen and monitor and for their ability to extract margins based on borrowers' travel times and competition. For this reason we focus our analysis of risk management incentives on two more specific proxies for probabilities of default and loss given default, before horse racing that with classical distance.

Going beyond simple borrower-lender distance and looking at the marginal contribution of each loan to the lender's portfolio risk, one possibility is for the lender to reduce risks to its portfolio by allocating more of its new lending to regions where default rates or collateral values are less correlated with those at home. In this vein, Quigley and van Order (1991) analyze how actual mortgage defaults in the US are correlated intra- and inter-regionally and infer that mortgage portfolios are indeed riskier if they are less regionally diversified.

On the other hand, a bank's risk managers may instead prefer to focus lending on fewer regions so that it pays to collect more information there. This argument is made by Loutskina and Strahan (2011) and empirically confirmed for the US market. Further, Favara and Giannetti (2017) show that a bank with many mortgages in the same region can better internalize the negative externalities of collateral liquidations on the prices of other nearby collateral in an episode of increased defaults, and likewise Favara and Giannetti (2017) and Giannetti and Saidi (2019) find an internalization of spill-overs from the liquidation of firm loans in more concentrated industries. This per se would speak in favor of seeking to sufficiently dominate one area in order to internalize and therefore ideally remove that externality.

To assess whether the benefits of hedging against idiosyncratic local risk or agency problems associated with greater distance dominate empirically, Goetz, Laeven, and Levine (2016) analyze the effects of US interstate branching deregulation and find that it does overall reduce

[11] In the same vein, Eichholtz et al. (2019) find US banks to increase margins in distance when pricing mortgages underlying Commercial Mortgage Backed Securities and interpret their measure of distance as a proxy for less soft information.

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 arguably 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.[12] 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. (2019). Therefore the context complies very much with one characterized by Stein (2002) as based fully on hard rather than soft information.[13] 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, or offer lower prices, when unemployment rates as proxies for default probabilities, or house values as proxies for loss given default, have historically exhibited a* ***lower correlation*** *between the applicant's and the bank's canton.*

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

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

2.3 Hypothesis 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. Further, 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,*

(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.[14] Importantly, there was no human broker intermediating between applicants and suppliers. This changed from 2013 when

[14] The Online Appendix examines how borrowers and lenders on the platform are representative of the full national market.

Comparis acquired human broker firm Hypoplus, but no human broker was involved during our sample period.[15] 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 as studied in (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 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 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.

[15] See https://www.hypoplus.ch/fr/hypotheken-news/item/in-eigener-sache/comparis-erhaelt-mit-hypoplus-eine-schwesterfirma-fuer-beratung.html in German or https://www.lenzstaehelin.com/en/news-events/deals-cases/comparisch-acquires-hypoplus-ag in English, both accessed in April 2021.

Offers can consist of between 1 and 3 tranches of different amounts, which may differ in the rate fixation period as well as in the offered interest rate. For each tranche, we subtract from the offered mortgage rate the swap rate for the same fixation period applicable on the day of the offer, as available through Bloomberg. This is to reflect the bank's refinancing costs absent any maturity transformation and is the measure of refinancing costs commonly used in the market under study, see also Basten (2020) and Basten and Mariathasan (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.[16] 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.

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

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

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%. The maximum is shaped by the fact that for any mortgage violating the self-regulatory requirement of at least 10% of "hard equity" (excluding pension wealth) from the household, the bank willing to provide it would have faced a regulatory risk weight of 100% instead of on average about 40%. The LTI ratio varied between 0.69 and 9.62, with a mean of 3.59. Household income varied between CHF 48,000 and 600,000, with a mean close to CHF 170,000, wealth including pension fund wealth reached an average close to CHF 500,000, and average age was 46 years.

Next, ***Table 1*** Panel (B) gives the key regional characteristics. The Herfindahl-Hirschmann Index (HHI) of cantonal mortgage market concentration ranges across the 26 cantons between 0.12 and 0.49, with a mean of 0.18 and a standard deviation of 0.05. In the years studied, it experienced year-on-year changes of between about -5 and +6pp with an average of -0.2pp. HHI based on national market shares, which we will need to construct our instrument, decreased by between 0.2 and 0.4pp in the years studied. The other component needed to construct our instrument, 2009 cantonal mortgage market shares of the Big Two combined, varied between about 9 and about 57%. The multi-market contact (competition) measure (MMC) of how many competitors in a canton a bank meets on average in how many other cantons ranges between 0.05 and 0.40 with an average of 0.07, while the number of online providers varies across cantons between 4 and 14 and averages 11. Finally, we see that house price growth varies between -4% and +15% with a mean around 4%.

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 (2020). On the liability side, the most important position for most banks are deposits, ranging between about 17% and 66% and averaging 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 responses, banks could draw on experience with between 0 and about 10'000 prior responses, with an average of about 4'000. Relevant for portfolio diversification, the inter-cantonal correlation of unemployment rates was on average 92%, but goes as low as 66% and has a high SD of about 68% reflecting enough potential to lower correlations in the portfolio. The inter-cantonal correlation of house price changes achieves a mean of 77% with a SD of 19%, but which goes as low as 15%. This reflects the fact that while real estate markets in all cantons are affected by the same interest rate, net immigration differs considerably due to different languages and so different source country compositions, as does regional economic specialization. The applying household was located between 0 and 175 km and on average about 21 km from the responding bank's nearest branch, both known to the level of about 4'400 zipcodes. We focus on geodesic distance, but note that GIS based driving distances or times available for a subsample yield very similar results. Applications received between 1 and 10 and on average a bit over 4 responses, which took about 97 hours or about 4 days. About 82% of all responses are offers, which are personal and binding conditional on the verification of the supplied information. The 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%, implying a mean spread above the swap rate for the same period of 90bps.

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 also discuss 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 market shares in cantonal mortgage volumes.[17] We start with simple non-causal logit regressions for the binary outcome offer and OLS regressions of the continuous outcome price first on the HHI level (***Table 2***) and then on the year-on-year HHI change ***(Table 3***). In each of the two tables, columns 1 and 2 control for both household and bank characteristics, columns 3 and 4 replace bank controls with bank fixed effects, and columns 5 and 6 also replace household controls with household group fixed effects. These groups are based on almost the full set of household characteristics, including their LTV bracket, their LTI bracket and an indicator for refinancing rather than new borrowing, as well as year and month fixed effects. Importantly though, other than in our risk management analyses below we cannot include here canton dummies, as these would be collinear with HHI.

One issue this creates is that different banks' prior presence as well as current online offer behavior may be influenced by the same unobservable. In particular, non-causal estimates are likely to be biased toward zero. For unobservable factors that increase the attractiveness of

[17] 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 at least traditionally many cantonal banks had mandates restricting which cantons (often their home plus directly neighboring ones) they could lend to, although more recently these restrictions were often loosened. In addition, many regional banks, much smaller than cantonal banks, had no formal restriction but preferred to stay in their home canton before hedonic models started facilitating property valuation also elsewhere.

lending to a certain canton are likely to have motivated more banks to start lending there in an offline world, thus reducing market concentration, and to incentivize more and more attractive offers also online. This could bias us to find more attractive offers going to less concentrated markets, thus biasing downward our estimates of interest.

To address this concern, we exploit the fact that precisely during the years of interest many 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 in cantons with higher initial market shares held by the Big Two.[18]

Accordingly, we instrument the year-on-year change in each cantonal mortgage market HHI with its Bartik or shift-share prediction, i.e., with the year-on-year change in the national level HHI (the *shift*) multiplied by the 2009 cantonal mortgage market *shares* of the Big Two. As revealed by our summary statistics, in the years of interest the HHI reduction at the national level varied between 0.2 and 0.4pp and averaged 0.3pp. The cantonal mortgage market share of the Big Two combined ranged between about 9% and about 57%. Our strategy thus compares the effect of the same shift in cantons with more than half of the market initially held by the Big Two to cantons with less than 10% held by them, and conceptually constructs the counterfactual of a canton with a zero market share and hence no impact of the Big Two mortgage lending reduction.

The strategy to thus 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 (2016), and Gete and Reher (2018). Chodorow-Reich also discusses how Credit Suisse was hit hard by losses in the US mortgage backed securities market and so had to reduce amongst others its US syndicated lending. In contrast to

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

those papers which focus on effects of losses or higher costs in the US on some segment of US lending, we exploit the fact that following their losses in the US the Swiss Big Two had to 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 also in Blickle (forthc.) and Brown, Guin, and Morkoetter (2020). The latter paper analyzes how households were quick to withdraw deposits from the Big Two, stressing the importance of bank household relationships. Blickle (forthc.) additionally exploits that where the Raiffeisen network of cooperative banks had branches close to UBS branches, significant portions of the deposit outflows from UBS went to Raiffeisen 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 *increase* their mortgage lending following the deposit inflows, UBS and CS had to *decrease* theirs following their deposit outflows. While the opportunities of the Big Two to borrow without collateral from banks without overseas losses or deposit withdrawals were limited, the Swiss National Bank (SNB) orchestrated an opportunity for them to issue additional covered bonds and so borrow against collateral through the so-called "Limmat transactions" in 2008 and 2009.[19] 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.[20] 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 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

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

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 prior market shares and other banks' current online bidding behavior. However, the *shift* caused by the Big Two's 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 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.

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

Finally, the move from probit to logit in turn means that implementing the 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 estimation through two-stage residual inclusion (2SRI). Here stage 2 includes the endogenous regressor itself, rather than its predictor, but it controls in stage 2 for the residuals from stage 1.

Letting subscript *i* denote individual households nested in household groups g, letting *b* denote banks, and $\widetilde{\Delta HHI}_i$ the prediction for ΔHHI_i based on our 1st stage, our 2SLS equation is

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

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

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

As the instrument can be understood as a shift-share instrument, robustness checks compute standard errors following Adão, Kolesár, and Morales (2019), even though their procedure currently allows to implement the 2nd stage as a linear model only.

Finally we remark that in an earlier version of this paper we used as endogenous regressor HHI levels rather than changes and as instrument its prediction, constructed as lagged levels plus the predicted shift-share changes used here. Results were qualitatively similar, but we acknowledge that that prediction was largely driven by lagged levels, the timing of which made reverse causality unlikely but did not suffice to rule omitted variable bias. Therefore our updated version uses HHI changes both for the instrument and for the endogenous regressor, while ***Tables 2-3*** show that the relationship of bank behavior with HHI levels and changes are similar.

4.2 Strategy on Risk Management

As discussed in the hypothesis section, distance between borrower and lender is likely to matter for many risk management decisions as a proxy for the lender's ability to use soft information. But first prior work such as Degryse and Ongena (2005) showed distance to matter also for borrower's willingness to pay, second diversification potential or soft information availability do not change monotonously in distance, and third soft information may matter less in some contexts than in others and can be ruled out in our setup. Therefore we decided to control for distance in some of our regressions, but focus on two measures arguably more relevant for banks' portfolio risk management. First, we use the correlation of unemployment rates between bank and borrower canton as a proxy for inter-regional complementarity of probabilities of default. Second, we use the correlation of house price changes between bank and borrower canton as a proxy for the inter-regional complementarity of loss given default. The latter 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. The 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. So we can summarize our analyses of banks' responses to geographical complementarity as follows:

$$Y_{h,b} = \alpha + \beta(Complement_{h,b}) + \delta X_h + \mu X_b + \tau(YMFE_h) + \varepsilon_{h,b} \quad (3)$$

In general this follows the specifications in Equations 1 and 2 on market concentration, except that the primary regressor of interest is now our measure of portfolio complementarity instead of the ΔHHI measure. As complementarity varies both within households and within banks, we can now use fixed effects for each household *h* rather than just for each household group *hg*. Therefore we do now not need to find a suitable instrument for the complementarity regressor. Our baseline measures of complementarity are the inter-cantonal correlations between unemployment rates and house price growth as explained above.

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 (2010). The latter find more discretion for loans that are smaller, unsecured or go to smaller and more opaque firms. This can be rationalized by the idea that decisions in these cases are harder to automate well. So they are more likely to be escalated to (senior) staff. In our context, all loans are mortgages and collateralized. But we expect more discretion 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:

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

These include again all household characteristics X_h, all bank characteristics X_b, market concentration in the applicant's canton HHI_h and $Complementarity_{h,b}$ between household h's and bank b's canton. In addition, we now include $Experience_{h,b}$, 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 4. 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.[21]

4.4 Standard Errors

Following Bertrand, Duflo, and Mullainathan (2004), at the baseline we cluster our standard errors by the panel dimension, i.e., by the 708 household groups for our market concentration analyses and by the 6,914 households for our risk management analyses. Robustness checks available on request, which cluster instead by the 7,442 bank * household zip code pairs, or by the 173 bank * household canton combinations, yield qualitatively the same results. All of these options have more than 50 clusters as recommended by Colin Cameron and Miller (2015) and

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

none of them contains more than 5% of observations, as recommended by Rogers (1993), both guidelines of which would be violated if we clustered by the 26 banks or 26 cantons only.

5 Results

Our results section is sctructured as follows.

First, in Subsection 5.1, ***Tables 2 and 3*** present our non-causal estimates of the association of bank responses with HHI levels and changes respectively. They show associations to be fairly stable across specifications, as well as robust to whether we use HHI levels or HHI changes. Following that, ***Table 4*** shows our baseline IV estimates using first 2SLS with linear 2nd stages and then 2SRI to allow also for non-linear 2nd stages. It also probes the robustness of our results to using AKM standard errors. Concluding our investigation of the role of market concentration alone, ***Table 5*** replaces the HHI measure of market concentration with the less common MMC measure. As the MMC measure depends on all cantons at the same time, it is not suitable for our IV strategy and so we investigate MMC without the ambition to prove causality.

Second, Subsection 5.2 starts in ***Table 6*** by investigating how banks respond to the complementarity of the applicant's canton with their own home canton in terms of unemployment rates as a key determinant of probabilities of default (PD), while ***Table 7*** measures complementarity instead as the inverse of correlations of house price growth given that house price changes have a major effect on loss given default (LGD). Following that, ***Table 8*** includes HHI changes and the two complementarity measures simultaneously to probe the robustness of each effect to controlling for the other. In contrast to ***Table 6*** and ***Table 7***, which can include fixed effects for each single household, ***Table 8*** must go back to household group fixed effects as in ***Table 3*** to avoid perfect collinearity with the instrument.

Third, in Subsection 5.3 we display our estimates of how much discretion banks retain in offering and pricing decisions beyond a common rule or automation.

Fourth, Subsection 5.4 discusses the coefficients obtained on various household and bank covariates. While we include these mainly as controls, their interpretation turns out to be interesting also on its own, and show the validity of our setup.

5.1 Results on Local Market Concentration

Table 2 starts with non-causal regressions of respectively offer dummy (columns 1, 3 and 5) and pricing (columns 2, 4 and 6) on the HHI level. Gradually increasing the conservativeness of our model, columns 1 and 2 use bank and household controls, 3 and 4 use bank fixed effects and household controls, and 5 and 6 use both bank and household group fixed effects as discussed above. While 1 and 3 have only few fixed effects and can hence use probit estimation, 5 must use logit instead of probit to avoid an incidental parameter problem. While line 1 displays the coefficients, the line below the constant shows the implied average marginal effects (AME) which coincide with the coefficients for the OLS estimation for pricing, but differ for probit and logit estimations. Finally, since a comparison of bank responses to perfect monopoly (HHI=1) to perfect competition (HHI=0) does not reflect the reality studied, at the bottom of the table we rescale the average marginal effects[22] by multiplying them with one standard deviation (SD) or 0.05 units of the HHI level. On these grounds, we find across all three specifications that a 1 SD increase in HHI levels is associated with an increase in offer propensities by about 1pp and a price discount of about 2bps, all statistically significant at the 1% level except for column 1 which is significant at the 10% level only.

Next, ***Table 3*** repeats the same procedure and setup but, in preparation of our IV estimations below, replaces HHI levels with HHI changes. Here OLS estimations of the effect on offer propensities are not statistically significant at conventional levels, but effects on pricing are and have the same size of about 2bps for a change in ΔHHI by 1SD or 0.0027 units.

After this preparation, ***Table 4*** presents our main IV estimations. Starting with column 1, we see that an increase in the predicted HHI change, the instrument, by 1pp, is associated with an increase in the HHI level by 3pp. This is in line with the fact that the total of all HHI changes has of course a much bigger variation than those predicted on the grounds of the Big Two

[22] For simplicity we speak of "effects" also when discussing Tables 2 and 3, although strictly speaking we discuss only associations here as explained in Section 4 above.

changes only. But importantly the first stage relationship is very strong even after including both bank and household group fixed effects, with a t statistic of close to 13 and correspondingly an F statistic of about 165.[23]

Columns 2 and 3 then show the resulting 2nd stage effects on offer propensity using 2SRI with logit and 2SLS with a linear probability model (LPM) respectively. The former, our methodological favorite, predicts an average marginal effect on offer propensity of about 6pp, while the latter predicts about 3pp. Both are clearly larger than the 1pp association implied by all non-causal estimations discussed above. This is in line with our reasoning above, whereby the same unobservables at the canton level are likely to have affected banks' eagerness to lend there offline and hence prior market concentration as well as affecting banks' current eargerness to lend to a canton online, thus causing non-causal estimates to be biased toward zero. Correspondingly, columns 4 and 5 also find pricing effects of about 5bps, compared to 2bps found with non-causal approaches.

Regardless of the methodology and resulting estimates, we remark that effects would be correspondingly larger if considering not a move in the HHI by 1 SD but by 10pp from the US Department of Justice upper threshold for a competitive market (15%) to the lower threshold for a concentrated market (25%). But we consider a change by 1 SD in our sample more relevant for the context studied. Relatedly, we can also rescale the changes by 1 SD of the respective outcome, i.e., by 0.38 for offer propensity and by 0.21 for pricing. The last line of the table shows that this suggests an elasticity of about 15% between a 1 SD change in ΔHHI and a 1 SD change in offer propensity, and an elasticity of about 25% for pricing. Concluding the description of Table 4, columns 5 and 6 show that statistical significance does not change much if we compute standard errors following Adão, Kolesár, and Morales (2019).

To convey the same relationships also visually, ***Figure 1*** groups the range of observed Δ(HHI) values into 20 bins containing an equal number of bank responses each. It then plots for each of these bins the corresponding average offer propensity in the upper panel or the average

[23] We remark that using as endogenous regressor HHI levels instead of changes yields expectedly a weaker but still significant F statistic of about 50, while replacing all fixed effects with controls reduces the F statistic to about 30.

spread offered in the lower panel respectively. To make the figure correspond to our estimations, both Δ(HHI) and the two outcomes are residualized for the same sets of controls as used in our regressions, i.e. both household group and bank fixed effects. The figure thus reveals also visually that more market concentration induces banks ceteris paribus to offer more often and at lower prices.

While the most common measure of market concentration is probably the HHI, another measure used e.g. in Degryse and Ongena (2007) is the measure of Multi-Market Contact or Competition (MMC). It sums the number of bank pairs present after 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 measure follows the idea in Edwards (1955) of a "linked oligopoly" under which multi-market contact increases banks' incentives to collude and hence leads them to behave less competitively. On the other hand, Park and Pennacchi (2009) find that the presence of more multi-market banks can *promote* more competitive behavior. So we need to look at the data to find out. Columns 1, 3 and 5 tell us that an increase in the MMC measure by 1 unit increases the offer propensity by 24-52pp, while columns 2, 4 and 6 find the same increase to additionally lower prices by 25-86bps, and except for column 5 all estimates are statistically significant at 1% or lower. This is more in line with the findings of Park and Pennacchi (2009), whereby multi-market contact promotes competitive behavior, than with the original "linked oligopoly" hypothesis of Edwards (1955) whereby it promotes collusion. We note though that since MMC is computed using information on all columns, it does not lend itself to instrumentation with our shift-share instrument given the cantonal variation in shares and so our MMC estimates are descriptive and not necessarily causal. Last, we foreshadow here that the results on banks' responses to prior market concentration are overall equally clear when we analyze them simultaneously with those to risk management incentives, as discussed in more detail below.

5.2 Results on Risk Management

As per our *Hypothesis 2*, ***Table 6*** 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.[24] As in ***Tables 2-3***, 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. These tell us that a bank would be up to 32% more likely to extend an offer, and give a discount of up to 33bps 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 2.3bps lower when the unemployment rate correlation is 1SD or 0.07 units lower.

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

Relatedly, ***Table 7*** replaces the complementarity measure based on unemployment rates with a measure based on house price growth, following the consideration that larger house price decreases in crises imply higher loss given default (LGD). Here we find that a change in complementarity by 1SD or 0.19 units increases the offer propensity by up to 1.14% and lowers the price by up to 1.14bps. These responses are somewhat smaller than those to unemployment rate complementarity. This makes sense insofar as ideally the bank wants to keep the PDs in its entire portfolio low. Use of remaining collateral values in a foreclosure procedure becomes

[24] 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.

necessary only conditional on default and in addition will at least imply additional costs even when collateral values still exceed the remaining debt. Hence PD complementaity seems yet more important than LGD complementarity.

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

Figure 2 conveys these results also visually. The two upper panels show bank responses to unemployment complementarity of applicant and bank canton as used in ***Table 6***, while the two lower panels show responses to house price change complementarity as used in ***Table 7***. In both cases, the left panel shows offer responses while the right one shows pricing responses. As in ***Figure 1***, variables on the horizontal axis are grouped into 20 equally sized bins to facilitate visibility, and in all four panels a linear line is fit using all about 25’000 underlying observations. The figure thus shows also visually how banks are more likely to offer and offer at lower margins when a loan to the applicant’s canton is more complementary to its own canton in terms of unemployment rates or house price changes respectively.

Next, ***Table 8*** investigates how well the effects of the two complementarity measures survive when combined with each other as well as with the (again instrumented) HHI change. To start with, the average marginal effect of HHI changes on offer propensities shrinks from about 22pp to about 12pp and that on pricing from about 17 to about 19bps, but both retain their full statistical significance so that the effects of market concentration survive controlling for what we view as risk management incentives. Next we look at responses to the two complementarity measures. In contrast to ***Table 6*** and ***Table 7*** we can now control only for household group rather than household fixed effects to avoid collinearity problems with the HHI change, which is why at the baseline we investigated the two issues separately. But the marginal effect of unemployment complementarity of 16-22pp is in the same range as the 10-32pp found in ***Table 6,*** while the average marginal effect on pricing takes the same size of about 25bps as there. The effect of house price change complementarity on offer propensity remains insignificant, while that on pricing remains again similar at now -7bps compared to -6bps in column 6 of ***Table 6***. Overall we can then conclude from ***Table 8*** that both the search for more better margins and that for better risk management survive when "horse racing" them against each other.

When observing that banks are more willing to offer, and offer better prices to regions whose unemployment rates or house price growth are less correlated with those in the bank's home canton, we have interpreted this as banks seizing the opportunity of lending without branches to improve their risk management. Of course we do not directly observe banks' reasoning behind their decisions and acknowledge that the arguable improvement in geographical diversification may also have come about without a conscious strife for it. But since either measure of complementarity is at least 18% correlated with branch distance, the above findings could alternatively be explained by banks charger higher (lower) prices to customers for having to drive shorter (longer) distances to the nearest branch, in line with the finding in Degryse and Ongena (2005), who find Belgian banks to charge lower borrowing rates to more distant firms.

To investigate this further, ***Table 9*** relates offer propensity and pricing to the distance between the applying household and the responding bank, both known to the level of about 4'400 Swiss zipcodes, while at the same time controlling for unemployment complementarity between the household's and the bank's canton. As in ***Table 2-3***, columns 1-2 include bank and household controls, columns 3-4 replace bank controls with bank fixed effects, and columns 5-6 additionally replace household controls with household group fixed effects. Since both branch distance and unemployment complementarity vary both within each bank and within each household, we can additionally include columns 7-8, which instead of a separate fixed effect for each of the 708 household groups can include even a separate fixed effect for each of the 6'914 households.

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

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

5.3 Results on Automation

As per our *Hypotheses 3a-c*, ***Table 10*** follows largely the same outline as ***Tables 2-3*** in terms of controls, and again columns with unequal numbers focus on offer decisions while those with equal numbers focus on pricing decisions. Now the regressions using the offer indicator or pricing themselves as outcome ("mean equations") are relegated to the online appendix and basically yield the coefficients on both HHI and risk relevant measures already discussed above. One interesting additional result worth highlighting here is that each 1'000 extra responses of experience are found to increase offer propensities by about 1pp, although the effect of experience on pricing is not robust to different specifications. But here we now use as left-hand side variables the log of the squared residual from those mean equations. Following amongst others (Cerqueiro, Degryse, and Ongena 2010), we interpret this as the amount of discretion used in offer and pricing decisions.

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. 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*.

Figure 3 portrays also visually in the upper panel the key coefficients, along with 95% confidence intervals, from ***Table 10***, column 1 on offer decisions and in the lower panel those from table column 2 on pricing decisions. Focusing on the less conservative versions with both household and bank characteristics rather than fixed effects here allows us to explicitly show also responses to thosem which seem interesting in their own right. The figure shows how for both decisions banks tend to exercise more discretion (less automation) when clients are riskier, and less discretion (more automation) when the bank itself is larger, more mortgage specialized, or has already accumulated more experience with the online platform.

One might be concerned that the heteroskedastic regression procedure estimates less discretion or more automation for one subgroup than for another merely because the former subgroup contains more observations and therefore exerts more influence on the one rule estimated. To address this concern, ***Appendix Tables 2-4*** repeat our estimations but now estimate respectively bank, calendar year, or experience year specific rules. The tables show robustness of our findings of more discretion for riskier applications, from smaller or less mortgage-specialized banks, for less concentrated markets, or for markets more complementary to those dominating the responder's portfolio. By contrast, the finding that discretion generally decreases with platform experience loses its robustness, with findings depending on the set of controls used.

Increasing automation can allow banks to cut operational costs. Admittedly we 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.

5.4 Coefficients on Other Household and Bank Characteristics

Here we also briefly discuss banks' responses to households' and banks' own characteristics, which can help to better understand the setup. For household characteristics we focus on indicators for LTV ratios above 67% and 80% and loan-to-income (LTI) ratios above 4.5 and 5.5 respectively. The specific LTI thresholds reflect frequent practice in the market[25] while

[25] 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

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

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

Looking at bank characteristics, we see that banks which are either larger in terms of total assets or have a larger fraction of their assets dedicated to mortgage lending offer more often and at lower prices. One plausible explanation of this finding, beyond risk management, is higher operational efficiency. By contrast, banks that raise a larger fraction of their funding through deposits offer less often. Here one possible reason is that having more depositors provides a bank already with a larger pool of potential mortgage clients, so that it may be less eager to sell

mortgage service payments ranging between 5.5% and 7.65% of the loan. The requirement for this to not exceed 1/3 was then equivalent to LTI thresholds of between 4.36 and 6.06. Here we round these to 4.5 and 5.5, as these are LTI cutoffs used in regulation in other countries such as the UK.

mortgages also online. Further, in contrast to the second most important source of funding for Swiss commercial banks, covered bonds, deposits have shorter contractually guaranteed rate fixation periods. Thus financing mortgages – the majority of which carries fixed rates – with deposits tends to yield a profitable margin in the short run, but implies also more interest rate risk to be borne or hedged at a cost. Further, better capitalized banks tend to charge higher prices, possibly reflecting that a larger fraction of funding raised through equity is typically thought to imply (more safety in crisis times but also) higher marginal costs per unit of lending. Finally worth mentioning here is that ***Appendix Table 1*** finds each 1'000 responses of online experience to increase offer propensities by about 1pp, thus capturing a dynamic component of participation in the online platform also beyond automation.

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 1 SD higher change in HHI, a bank is about 6pp more likely to make an offer and in addition is willing to lower its price by up about 5bps. This finding may be counter-intuitive prima facie to some readers, who may have expected higher concentration to allow banks making *less* attractive offers. But more concentrated markets also offer online bidders the chance to get "a foot in the door" in markets with in expectation more attractive future business. For potential borrowers located in such hitherto more concentrated markets, this implies that the availability of an online platform can lead to more and better mortgage offers.

We have obtained these findings by instrumenting actual changes in cantonal market concentration with those predicted to follow from the domestic mortgage lending contractions of the Big Two, UBS and CS, after they suffered severe losses in the US subprime crisis. In particular, we exploit these developments with a type of shift-share instrument, multiplying Switzerland-wide shifts in HHI levels with earlier Big Two market shares in each canton.

Second, banks offer about 2% (1%) more often and in addition reduce their prices by about 2bps (1bps) more if the applicant's canton has a 1SD lower unemployment rate (house price change) correlation with the bank's own canton. 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 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.

Third, we investigate the discretion banks retain around estimated decision rules and interpret it as cases in which decision-making is not yet fully automated or is even escalated to more senior staff. As expected, we find more automation for safer loans, by larger banks, and by banks more specialized in mortgage lending. We also find that discretion decreases or automation increases the more online responses the bank has already sent out. This suggests that longer participation 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. But we do 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.

We do not observe explicitly how the studied online behavior changes balance sheets, riskiness or profitability of entire banks or the entire market. In fact, behavior on this platform in the years studied alone seems unlikely to do so given the limited platform size. However, as indicated above the benefits of the platform to both lenders and borrowers have meanwhile motivated more and bigger banks and non-banks to participate in or even operate their own platforms. Therefore it seems reasonable to assume that this development can over time also affect the entire market. This paper has analyzed this in an unusually clean way.

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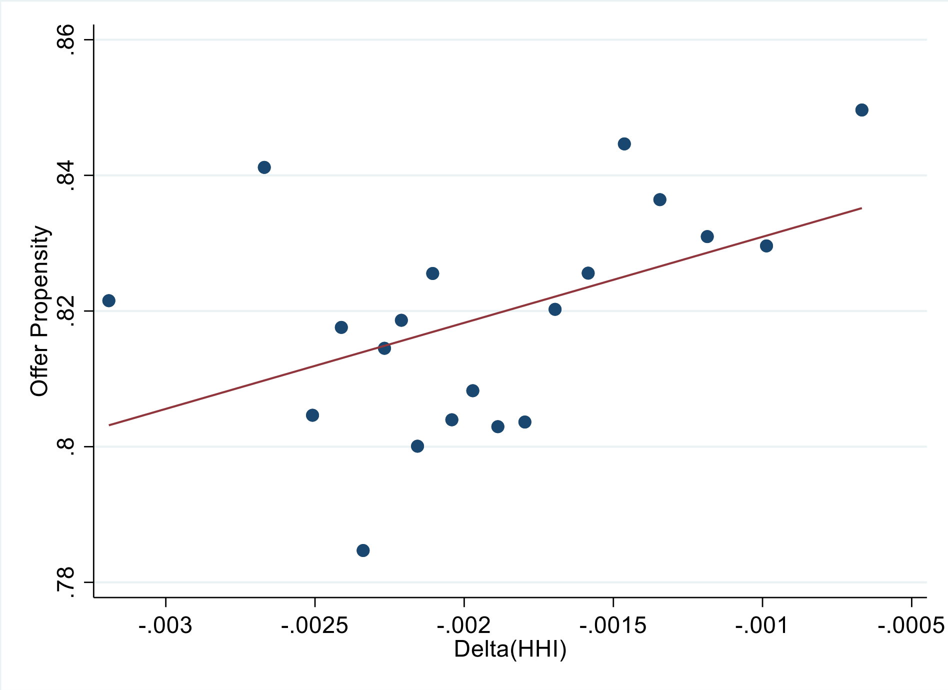
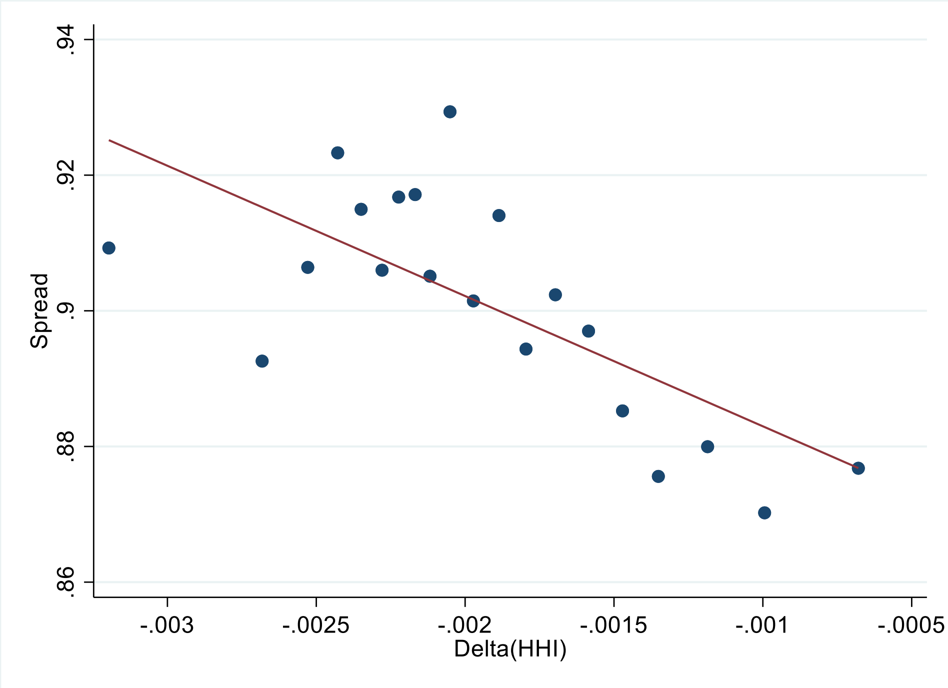
Figures and Tables

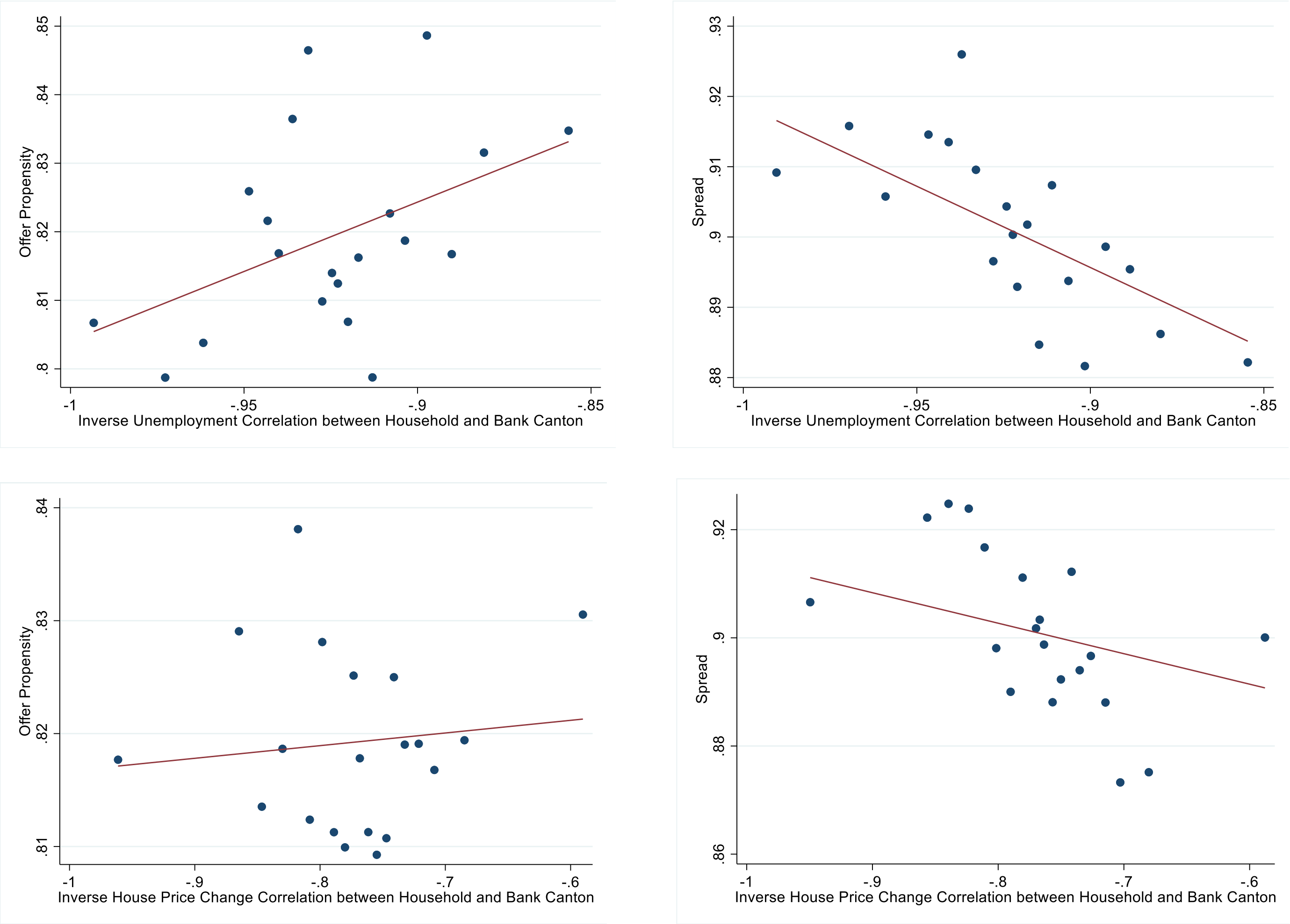
Figure 1: Bin Scatter Plots for Offer Propensity and Pricing against Δ(HHI)





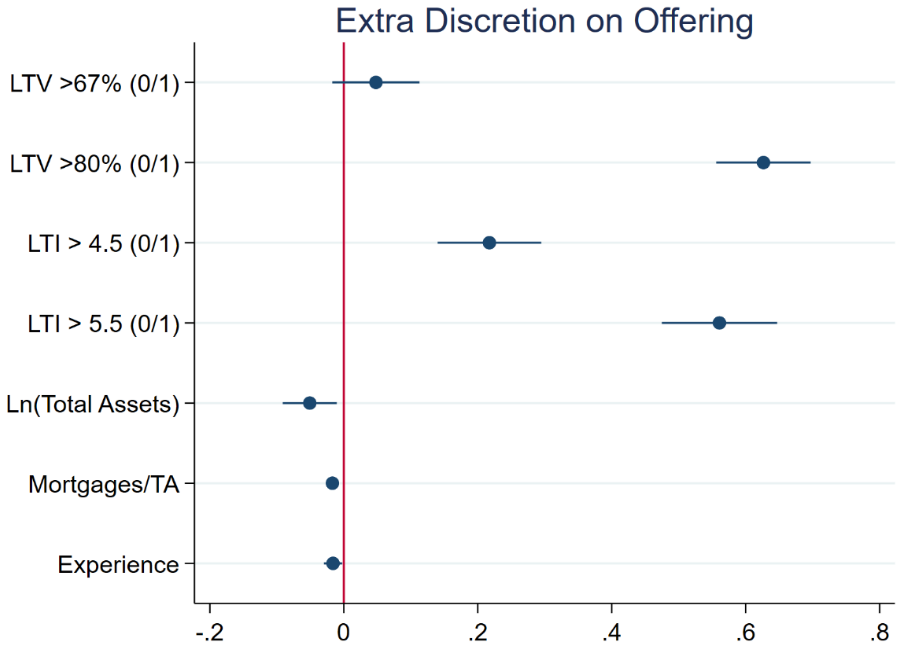
The upper panel plots average offer propensities against average values for Δ(HHI) for 20 equally sized (by the number of bank responses) bins of Δ(HHI) values. The lower panel does the same for the outcome weighted spread, see e.g. the notes of ***Tables 2-4*** for more details. Both panels residualize the averages for the same set of controls as used in our regressions using linear estimation.

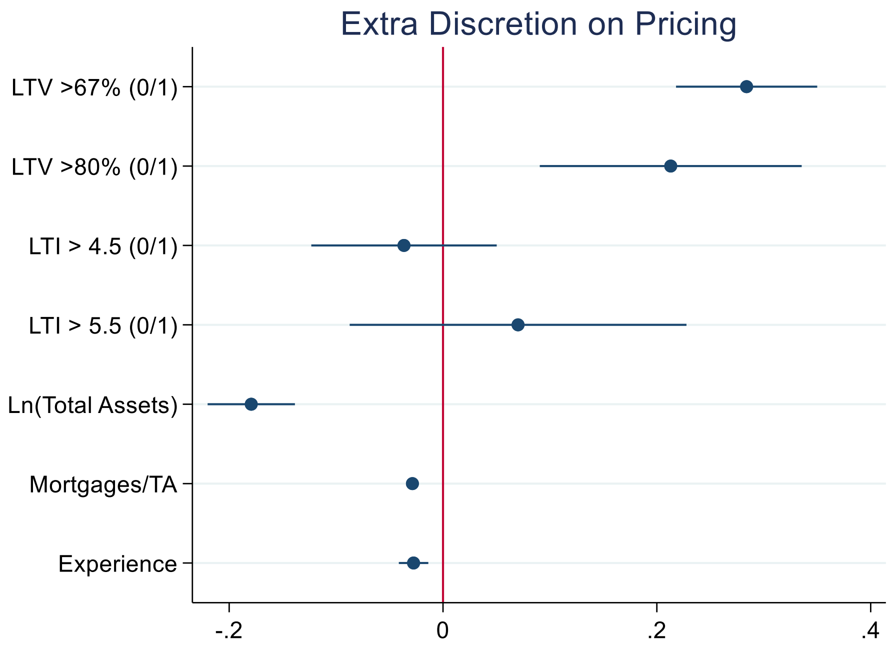
Figure 2: Bin Scatter Plots for Offer Propensity and Pricing against Portfolio Complementarity



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

Figure 3: Selected Coefficients from our Automation Analyses in Table 10





The upper panel, for discretion on Offering, shows selected coefficients from ***Table 10***, column 1, along with 95% confidence intervals. The bottom panel for discretion on Pricing, shows selected coefficients from ***Table 10***, column 2, along with 95% confidence intervals.

Table 1: Descriptive Statistics

	N	Mean	SD	Min	Max
(A) Applicant Characteristics					
Year	25'125	2'011	1	2'010	2'013
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	0.540	0.500	0.000	1.000
Loan-to-Value (LTV)	25'125	64.500	17.300	15.000	90.000
I (LTV > 67%)	25'125	0.530	0.500	0.000	1.000
I (LTV > 80%)	25'125	0.080	0.260	0.000	1.000
Loan-to-Income (LTI)	25'125	3.590	1.520	0.690	9.620
I (LTI > 4.5)	25'125	0.230	0.420	0.000	1.000
I (LTI > 5.5)	25'125	0.080	0.270	0.000	1.000
Household Total Income	25'125	167'603	88'961	48'000	600'000
Household Wealth incl. Pension Fund	25'125	469'333	515'877	10'000	3'180'000
Applicant Age	25'125	46	10	28	73
(B) Regional Characteristics					
Herfindahl-Hirschmann Index (HHI)	25'125	0.180	0.050	0.120	0.490
ΔHHI	25'125	-0.002	0.003	-0.052	0.055
Δ(Federal HHI)	25'125	-0.003	0.001	-0.004	-0.002
Big Two Cantonal Mortgage Share 2009 in %	25'125	30.657	8.482	9.129	56.911
Multi-Market Contact (MMC) Index	25'125	0.070	0.030	0.050	0.400
Number of Online Providers (NOP)	25'125	10.920	2.520	4.000	14.000
Single-Family Home Price Growth	25'125	4.070	4.070	-3.990	15.270
(C) Bank Characteristics					
Bank Total Assets (TA)	25'125	16’932	12’841	434	37’804
Mortgages/TA	25'125	69.820	10.430	39.790	90.620
Deposits/TA	25'125	47.800	17.900	16.720	65.630
Capital Ratio	25'125	7.250	1.030	4.720	11.330
(D) Interaction Characteristics					
Experience in 1'000 Web Responses	25'125	4.073	2.939	0.001	10.153
Correlation of Unempl. Rates 1973-2019	25'125	0.920	0.660	0.680	1.000
House price growth correlation	25'125	0.770	0.190	0.150	1.000
Branch Distance in km	25'544	20.861	24.970	0.000	174.798
Responses per Application	25'125	4.240	1.450	1.000	10.000
Response Time in Hours	25'125	97.410	151.720	-2.730	789.100
I (Offer = 1)	25'125	0.820	0.380	0.000	1.000
Weighted Spread Offered	20'583	0.900	0.210	0.490	1.520

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

Table 2: Non-Causal Analysis of Bank Responses and Market Concentration Levels

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
HHI	0.48*	-0.39***	0.83***	-0.46***	1.22***	-0.46***
	(0.28)	(0.05)	(0.29)	(0.05)	(0.43)	(0.03)
I(LTV>=67%)	-0.05	0.05***	-0.05	0.05***		
	(0.03)	(0.01)	(0.03)	(0.01)		
I(LTV>=80%)	-0.84***	0.00	-0.86***	0.00		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(LTI>=4.5)	-0.19***	0.01	-0.18***	0.01		
	(0.03)	(0.01)	(0.03)	(0.01)		
I(LTI>=5.5)	-0.84***	0.02	-0.84***	0.02*		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.10***	0.03**	0.10***	0.03**		
	(0.03)	(0.01)	(0.03)	(0.01)		
House price growth	0.64	-1.16***	0.89*	-1.15***		
	(0.45)	(0.16)	(0.47)	(0.15)		
Number of Web Providers	0.02***	-0.01***	0.02***	-0.01***		
	(0.01)	(0.00)	(0.01)	(0.00)		
Ln(Total Assets)	0.06***	-0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.01***	-0.00***				
	(0.00)	(0.00)				
Deposits/TA	-0.02***	0.00				
	(0.00)	(0.00)				
Equity/TA	0.02**	0.02***				
	(0.01)	(0.00)				
Constant	-0.18	1.37***	0.75***	1.12***		1.01***
	(0.23)	(0.05)	(0.23)	(0.02)		(0.02)
d(y)/d(HHI)	0.11*	-0.39***	0.19***	-0.46***	0.29***	-0.46***
	(0.07)	(0.05)	(0.07)	(0.05)	(0.10)	(0.03)
Observations	25’125	20’583	25’113	20’583	24’428	20’583
R2		0.13		0.19		0.14
Estimation	Probit	OLS	Probit	OLS	Logit	OLS
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
Effect of 1SD of HHI	0.01	-0.02	0.01	-0.02	0.01	-0.02

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

Table 3: Non-Causal Analysis of Bank Responses and Market Concentration Changes

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
ΔHHI	-4.29	-6.67***	-4.43	-6.18***	2.50	-2.13***
	(4.04)	(0.92)	(4.06)	(0.88)	(6.92)	(0.48)
I(LTV>=67%)	-0.05	0.05***	-0.05	0.05***		
	(0.03)	(0.01)	(0.03)	(0.01)		
I(LTV>=80%)	-0.84***	0.00	-0.85***	0.00		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(LTI>=4.5)	-0.18***	0.01	-0.18***	0.00		
	(0.03)	(0.01)	(0.03)	(0.01)		
I(LTI>=5.5)	-0.84***	0.02*	-0.84***	0.03**		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.10***	0.03**	0.10***	0.03**		
	(0.03)	(0.01)	(0.03)	(0.01)		
House price growth	0.81*	-1.34***	1.11**	-1.33***		
	(0.43)	(0.15)	(0.45)	(0.14)		
Number of Web Providers	0.02***	-0.00***	0.02***	-0.00***		
	(0.01)	(0.00)	(0.01)	(0.00)		
Ln(Total Assets)	0.06***	-0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.01***	-0.00***				
	(0.00)	(0.00)				
Deposits/TA	-0.02***	0.00**				
	(0.00)	(0.00)				
Equity/TA	0.03**	0.02***				
	(0.01)	(0.00)				
Constant	-0.16	1.31***	0.93***	0.99***		0.92***
	(0.23)	(0.05)	(0.22)	(0.02)		(0.02)
d(y)/d(ΔHHI)	-1.02	-6.67***	-1.03	-6.18***	0.57	-2.13***
	(0.96)	(0.92)	(0.94)	(0.88)	(1.59)	(0.48)
Observations	25’125	20’583	25’113	20’583	24’428	20’583
R2		0.13		0.19		0.13
Estimation	Probit	OLS	Probit	OLS	Logit	OLS
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
Effect of 1SD of ΔHHI	n/s	-0.02	n/s	-0.02	n/s	-0.01

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. ΔHHI is the year-on-year change therein. 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. Standard errors in parentheses are clustered by household group. * $p<0.1$, ** $p < 0.05$, *** $p<0.01$.

Table 4: Instrumental Variable (IV) analysis of Bank Responses to Market Concentration

Dependent Variable	(1) ΔHHI 1st Stage	(2) I(Offer) 2SRI	(3) I(Offer) 2SLS	(4) Price 2SLS	(5) Offer 2SLS AKM	(6) Price 2SLS AKM
ΔHHI		96.11***				
		(29.47)				
$\widehat{\Delta \mathrm{HHI}}$			12.68***	-19.34***	12.68***	-19.34***
			(3.73)	(1.99)	(3.67)	(1.96)
Instrument	2.98***					
	(0.23)					
1st Stage Residual		-99.55***				
		(30.42)				
Constant	0.00**		0.89***	0.91***	0.06	0.67***
	(0.00)		(0.04)	(0.02)	(0.06)	(0.05)
d(y)/d(ΔHHI)		21.70***	12.68***	-19.34***	12.68***	-19.34***
		(6.54)	(3.73)	(1.99)	(3.67)	(1.96)
Observations	25,125	24,428	25,125	20,583	25,125	20,583
HH Groups	708	578	708	654	708	654
F statistic	165.4					
Method	OLS	Logit	LPM	OLS	LPM	OLS
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
HH Group FE	Yes	Yes	Yes	Yes	Yes	Yes
dSD(ΔHHI) / d(SD(z)=0.0003)	0.33***					
dy / d(SD(ΔHHI)=0.0027)		0.06***	0.03***	-0.05***	0.03***	-0.05***
dSD(y) / d(1SD(ΔHHI)=0.0027)		0.15***	0.09***	-0.25***	0.09***	-0.25***

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. ΔHHI is the year-on-year change therein, $\widehat{\Delta HHI}$ its prediction based on the 1st stage coefficients.

Column 1 shows the first-stage regression of ΔHHI on the instrument. Column 2 shows the 2nd stage for the binary outcome offer, combining logit with 2-stage residual inclusion (2SRI). Column 3 analyzes the same effect combining a linear probability model (LPM) with two-stage least squares (2SLS), while column 4 uses the same combination for the continuous outcome pricing. Columns 5 and 6 repeat the estimations from columns 3 and 4 respectively, but compute standard errors following Adao, Kolesar and Morales (2009). Below the constant we display the average marginal effects of moving from perfect competition (HHI=0= to perfect monopoly (HHI=1). At the bottom, we rescale these effects more realistically by the standard deviation (SD) of ΔHHI, 0.0027, and also express that effect as an elasticity to a 1SD change in the respective column's outcome variable. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

Table 5: Bank Responses and Multi-Market Competition

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
MMC	1.17**	-0.86***	2.28***	-0.73***	1.02	-0.25***
	(0.46)	(0.06)	(0.52)	(0.06)	(0.70)	(0.05)
I(LTV>=67%)	-0.05*	0.05***	-0.05*	0.05***		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTV>=80%)	-0.85***	0.02***	-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	-0.50	-0.53***	0.27	-0.59***		
	(0.70)	(0.08)	(0.74)	(0.08)		
Number of Web Providers	0.03***	-0.01***	0.03***	-0.01***		
	(0.01)	(0.00)	(0.01)	(0.00)		
Ln(Total Assets)	0.07***	-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	-0.59**	1.74***	0.50*	1.22***		0.94***
	(0.29)	(0.05)	(0.28)	(0.03)		(0.02)
d(y)/d(MMC)	0.27**	-0.86***	0.52***	-0.73***	0.24	-0.25***
	(0.11)	(0.06)	(0.12)	(0.06)	(0.16)	(0.05)
Observations	25’125	20’583	25’113	20’583	24’428	20’583
R2		0.32		0.36		0.13
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
Std Error Cluster	Bank*HHZip	Bank*HHZip	Bank*HHZip	Bank*HHZip	Robust	Robust

MMC is the measure of Multi-Market Contact or Competition. It measures how many competitors in a canton a bank meets on average in how many other cantons. As in Tables 2 and 3, 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. Standard errors in parentheses are clustered by household group. * p<0.1, ** p < 0.05, *** p<0.01.

Table 6: Risk Management through Unemployment Complementarity

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
Unemployment Complementarity	1.36***	-0.33***	0.64***	-0.24***	2.41***	-0.25***
	(0.21)	(0.03)	(0.24)	(0.03)	(0.66)	(0.03)
HHI	0.17	-0.39***	0.49*	-0.43***		
	(0.26)	(0.03)	(0.27)	(0.03)		
I(LTV>=67%)	-0.05*	0.05***	-0.05*	0.05***		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTV>=80%)	-0.84***	0.02***	-0.85***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(LTI>=4.5)	-0.18***	-0.00	-0.17***	0.00		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTI>=5.5)	-0.86***	0.03***	-0.86***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.09***	0.02***	0.09***	0.02***		
	(0.03)	(0.00)	(0.03)	(0.00)		
Ln(Total Assets)	0.03**	-0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.02***	-0.00***				
	(0.00)	(0.00)				
Deposits/TA	-0.01***	0.00*				
	(0.00)	(0.00)				
Equity/TA	0.07***	0.01***				
	(0.01)	(0.00)				
Constant	0.90***	1.31***	1.67***	0.85***		0.72***
	(0.29)	(0.05)	(0.35)	(0.04)		(0.04)
d(y)/d(Complementarity)	0.32***	-0.33***	0.15***	-0.24***	0.10*	-0.25***
	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)
Observations	25’060	20’533	25’048	20’533	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 7: Risk Management through House Price Change Complementarity

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price
House price change complementarity	0.24***	-0.03***	0.05	-0.05***	-0.05	-0.06***
	(0.07)	(0.01)	(0.09)	(0.01)	(0.26)	(0.01)
HHI	0.20	-0.40***	0.59**	-0.42***		
	(0.25)	(0.03)	(0.27)	(0.03)		
I(LTV>=67%)	-0.05*	0.05***	-0.05*	0.05***		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTV>=80%)	-0.84***	0.02***	-0.85***	0.03***		
	(0.04)	(0.01)	(0.04)	(0.01)		
I(LTI>=4.5)	-0.17***	-0.00	-0.17***	0.00		
	(0.03)	(0.00)	(0.03)	(0.00)		
I(LTI>=5.5)	-0.86***	0.03***	-0.87***	0.03***		
	(0.05)	(0.01)	(0.05)	(0.01)		
I(New Mortg.=1)	0.09***	0.02***	0.09***	0.02***		
	(0.03)	(0.00)	(0.03)	(0.00)		
Ln(Total Assets)	0.03**	-0.04***				
	(0.01)	(0.00)				
Mortgages/TA	0.01***	-0.00***				
	(0.00)	(0.00)				
Deposits/TA	-0.01***	0.00***				
	(0.00)	(0.00)				
Equity/TA	0.05***	0.01***				
	(0.01)	(0.00)				
Constant	0.02	1.54***	1.05***	1.04***		0.90***
	(0.24)	(0.03)	(0.26)	(0.03)		(0.02)
d(y)/d(Compl)	0.06***	-0.03***	0.01	-0.05***	-0.01	-0.06***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.05)	(0.01)
Observations	25’125	20’583	25’113	20’583	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 8: Risk Management and Responses to Market Concentration Combined

	(1) Offer	(3) Price	(4) Offer	(6) Price	(7) Offer	(9) Price
ΔHHI	87.24***		94.16***		92.28***	
	(29.75)		(30.46)		(29.91)	
$\widehat{\Delta HHI}$		-16.89***		-16.92***		-16.73***
		(2.60)		(2.69)		(2.64)
Unemp. Complementarity (UC)	1.12**	-0.26***			1.73***	-0.25***
	(0.46)	(0.03)			(0.58)	(0.04)
HP Change Complementarity (HPCC)			0.09	-0.07***	-0.37*	-0.01
			(0.17)	(0.01)	(0.21)	(0.02)
1st Stage Residual	-91.89***		-97.68***		-97.19***	
	(30.72)		(31.40)		(30.91)	
Constant		0.65***		0.84***		0.65***
		(0.04)		(0.02)		(0.04)
d(y)/d(ΔHHI)	12.77**	-16.89***	20.90***	-16.92***	11.65**	-16.73***
	(6.11)	(2.60)	(6.99)	(2.69)	(5.87)	(2.64)
d(y)/d(UC)	0.16***	-0.26***			0.22***	-0.25***
	(0.04)	(0.03)			(0.04)	(0.04)
d(y)/d(ΔHPCC)			0.02	-0.07***	-0.05*	-0.01
			(0.04)	(0.01)	(0.03)	(0.02)
Observations	24’326	20’533	24’428	20’583	24’326	20’533
HH Groups	575	653	578	654	575	653
Estimation	2SRI Logit	IV	2SRI Logit	IV	2SRI Logit	IV
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FE	No	No	No	No	No	No
HH Group FE	Yes	Yes	Yes	Yes	Yes	Yes

ΔHHI and $\widehat{\Delta HHI}$ as in Table 4, Unemployment and House Price Change Complementarity as in Table 6 and Table 7 respectively. Standard errors in parentheses are clustered by household. * p<0.1, ** p < 0.05, *** p<0.01.

Table 9: Bank Responses and the Distance of the Client to the Bank's Nearest Branch

	(1) Offer	(2) Price	(3) Offer	(4) Price	(5) Offer	(6) Price	(7) Offer	(8) Price
Branch Distance (BD) in 100km	-0.17***	-0.02***	-0.23***	-0.05***	-0.35***	-0.05***	-0.50***	-0.06***
	(0.04)	(0.01)	(0.05)	(0.01)	(0.08)	(0.01)	(0.10)	(0.01)
Unemployment Complementarity	1.71***	-0.35***	0.74***	-0.24***	1.24***	-0.35***	2.14***	-0.23***
	(0.22)	(0.03)	(0.27)	(0.03)	(0.42)	(0.04)	(0.55)	(0.03)
I(LTV>=67%)	-0.08***	0.05***	-0.08***	0.05***				
	(0.03)	(0.00)	(0.03)	(0.00)				
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	-0.17***	0.01				
	(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)	0.12***	0.02***	0.12***	0.02***				
	(0.03)	(0.00)	(0.03)	(0.00)				
House price growth	-1.46	-0.20**	-0.86	-0.13				
	(1.06)	(0.10)	(1.07)	(0.10)				
Number of Web Providers	0.01	-0.01***	0.02	-0.01***				
	(0.01)	(0.00)	(0.01)	(0.00)				
Ln(Total Assets)	0.02	-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	0.06***	0.01***						
	(0.01)	(0.00)						
Constant	1.72***	1.34***	1.77***	0.91***	2.75***	0.58***	4.67***	0.73***
	(0.39)	(0.04)	(0.43)	(0.05)	(0.55)	(0.04)	(0.69)	(0.04)
d(y)/d(BD)	-0.04***	-0.02***	-0.05***	-0.05***	-0.35***	-0.05***	-0.50***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.08)	(0.01)	(0.10)	(0.01)
Observations	25’479	20’851	25’467	20’851	25’467	20’851	25’467	20’851
Bank Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
HH Group Fixed Effects	No	No	No	No	Yes	Yes	No	No
Individual HH Fixed Effects	No	No	No	No	No	No	Yes	Yes
Estimation	Probit	OLS	Probit	OLS	Logit	OLS	Logit	OLS

Branch Distance (BD) is the distance in 100km between from the applicant’s zipcode to the closest branch of the responding bank. Unemployment Complemetarity as in Table 6 above. 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 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, 5-6 also replace household controls with household group fixed effects, 7-8 with individual household fixed effects. Standard errors in parentheses are clustered by household. * p<0.1, ** p < 0.05, *** p<0.01.

Table 10: 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)
Unemployment Complementaity	-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 2-3, but add “Experience” as the number of online mortgage applications (In 1’000) the responding bank has already processed since the platform start in 2008. In the Online Appendix we display the underlying mean equation relating offers and prices to these regressors. Here we display the variance equation relating the log of the squared residual from the mean equation to the regressors of interest. Standard errors in parentheses are robust. * p<0.1, ** p < 0.05, *** p<0.01.

Online Appendix

In this Online Appendix, Section 1 briefly discusses ***Appendix Tables 1-4*** with additional material on our automation analyses. Following that, Section 2 discusses ***Appendix Tables 5-7***, which investigate the representativeness of our sample for the Swiss mortgage market in general.

A1. Background Material on Automation Estimations

Appendix Table 1 shows our estimations of the mean equations, the logged and squared residuals of which we used as left-hand-side variable for estimating the variance equations in ***Table 10*** of our main paper. Results on average bank responses to market concentration, risk management and controls correspond qualitatively to those in ***Tables 2-9*** of our main paper. So we include the mean equation estimations for ***Table 10*** here only for completeness and keep our discussion short. We confirm that we observe higher offer propensities and lower spreads in responses to more concentrated markets and to markets more complementary to the responding bank's prior portfolio, as well as to applications with lower credit risk and from larger or more mortgage-specialized banks. We also observe offer propensity to increase by 1 pp with each 1'000 responses already sent out, although prices do not unambiguously become higher or lower with experience.

Following this presentation of our main mean equations, ***Appendix Tables 2-4*** repeat the estimations from ***Table 10*** but now estimate respectively bank, calendar year, or experience year specific rules. This is to address the concern that the heteroskedastic regression procedure might estimate less discretion or more automation for one subgroup than for another merely because the former subgroup contains more observations and so exerts more influence on the one rule estimated. But ***Appendix Tables 2-3*** show robustness of our findings of more discretion for riskier applications, from smaller or less mortgage-specialized banks, for less concentrated markets, or for markets more complementary ones to those dominating the responding bank's portfolio. By contrast, the finding that discretion generally decreases with platform experience loses its robustness, with findings depending on the set of controls used.

A2. Sample Representativeness

An important question when analyzing data from online lending is how representative these are of the offline market. To start with, ***Appendix Table 5*** presents the distribution of all 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, ***Appendix Table 6*** contrasts the geographical distribution of the headquarters of the banks in our sample with that of the universe of Swiss retail banks used in Basten (2020). That paper starts out from the universe of all Swiss banks and then zooms in on 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 the lower number of banks observed here. 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 sufficiently 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 likely also representative of that in larger countries.

Finally, ***Appendix Table 7*** 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

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

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 (2020). 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, due to 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.

As explained in the main paper, given prepayment penalties a Swiss mortgage is often a decision for 10 or more years, making it more worthwhile to “shop around” for the best offer. Traditionally, this required visiting several nearby bank branches, whereas now responses from a larger number of banks from across the country can be obtained online. It still seems reasonable to expect that those households who use that opportunity may be more price-sensitive, but they do not appear to differ from the average mortgage borrower in terms of risk characteristics. Further, as borrowers need not borrow from the limited number of banks who have a branch nearby, unlike the firms switching banks after branch closures in Bonfim, Nogueira, and Ongena (forthcoming), they are arguably in a better position to exploit the existing competition.

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.

References

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Snb. 2014. *Financial Stability Report 2014*. Berne: Swiss National Bank.

Appendix Table 1: Mean Equations Underlying the Automation Analysis

	(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.

Appendix Table 2: Automation with Bank-Specific Rules

	(1) Offer Discretion	(2) Spread Discretion	(3) Offer Discretion	(4) Spread Discretion	(5) Offer Discretion	(6) Spread Discretion
I(LTV>=67%)	0.05	0.54***	0.05	0.40***		
	(0.03)	(0.13)	(0.03)	(0.12)		
I(LTV>=80%)	0.66***	-0.04	0.70***	-0.04		
	(0.04)	(0.13)	(0.04)	(0.13)		
I(LTI>=4.5)	0.22***	0.03	0.24***	0.02		
	(0.04)	(0.13)	(0.04)	(0.11)		
I(LTI>=5.5)	0.59***	0.06	0.62***	0.13		
	(0.05)	(0.17)	(0.05)	(0.17)		
I(New Mortg.=1)	-0.24***	-0.11	-0.25***	-0.08		
	(0.03)	(0.13)	(0.03)	(0.12)		
Ln(Total Assets)	0.03	-0.17***				
	(0.02)	(0.04)				
Mortgages/TA	-0.02***	-0.03***				
	(0.00)	(0.01)				
Deposits/TA	0.01***	0.02***				
	(0.00)	(0.01)				
Equity/TA	-0.07***	-0.00				
	(0.02)	(0.04)				
HHI	-1.13***	-0.29	-1.27***	-0.42		
	(0.34)	(0.82)	(0.38)	(0.99)		
HP Growth	-2.02***	0.42	-1.71***	-2.35*		
	(0.55)	(1.28)	(0.58)	(1.24)		
Number Providers	-0.04***	-0.04**	-0.05***	-0.08***		
	(0.01)	(0.02)	(0.01)	(0.02)		
Unemp. Compl.	-1.54***	-0.68	-1.04***	1.59	-2.21***	-4.22***
	(0.34)	(0.77)	(0.38)	(1.09)	(0.25)	(0.60)
Experience	-0.01	0.02	0.00	-0.14***	0.01	0.12***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)
Constant	-2.12***	-1.33	-2.34***	-1.98*	-2.02***	-3.34***
	(0.46)	(1.12)	(0.50)	(1.16)	(0.01)	(0.05)
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 repeats the estimations of the variance equation with different sets of controls displayed in Table 10 of the main paper, but now probes the robustness of that procedure to using underlying mean equations (also available on request) that are bank specific. Standard errors in parentheses are robust. * p<0.1, ** p < 0.05, *** p<0.01.

Appendix Table 3: Automation with Calendar-Year-Specific Rules

	(1) Price	(2) Discretion	(3) Price	(4) Discretion	(5) Price	(6) Discretion
I(LTV>=67%)	0.05***	0.50***	0.05***	0.49***	0.05***	0.49***
	(0.01)	(0.18)	(0.01)	(0.17)	(0.01)	(0.17)
I(LTV>=80%)	0.05***	-0.01	0.05***	0.01	0.06***	-0.04
	(0.02)	(0.19)	(0.02)	(0.18)	(0.02)	(0.19)
I(LTI>=4.5)	0.03**	0.03	0.02*	0.02	0.03**	-0.01
	(0.01)	(0.16)	(0.01)	(0.16)	(0.01)	(0.16)
I(LTI>=5.5)	0.03*	0.02	0.03**	0.02	0.03**	-0.00
	(0.01)	(0.20)	(0.01)	(0.20)	(0.01)	(0.20)
I(New Mortg.=1)	0.01	-0.03	0.01	-0.02	0.01	0.01
	(0.01)	(0.17)	(0.01)	(0.16)	(0.01)	(0.17)
Ln(Total Assets)		-0.22***		-0.20***		-0.25***
		(0.04)		(0.04)		(0.04)
Mortgages/TA		-0.03***		-0.03***		-0.03***
		(0.01)		(0.01)		(0.01)
Deposits/TA		0.02***		0.03***		0.02***
		(0.01)		(0.01)		(0.01)
Equity/TA		0.04		0.02		0.06
		(0.03)		(0.03)		(0.03)
HHI	-0.50***	-1.22				
	(0.07)	(0.83)				
HP Growth	0.21	0.10				
	(0.14)	(2.38)				
Number Providers	-0.01***	-0.04**				
	(0.00)	(0.02)				
Unemp. Compl.			-0.07***	0.05		
			(0.01)	(0.22)		
Experience					0.00***	-0.01*
					(0.00)	(0.01)
Constant	0.88***	-0.25	0.70***	-0.78	0.72***	-0.06
	(0.02)	(0.78)	(0.01)	(0.82)	(0.01)	(0.76)
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 repeats the estimations of the variance equation with different sets of controls displayed in Table 10 of the main paper, but now probes the robustness of that procedure to using underlying mean equations (also available on request) that are calendar year specific. Standard errors in parentheses are robust. * p<0.1, ** p < 0.05, *** p<0.01.

Appendix Table 4: Automation with Experience-Year-Specific Rules

	(1) Price	(2) Discretion	(3) Price	(4) Discretion	(5) Price	(6) Discretion
I(LTV>=67%)	0.07	0.48***	0.07*	0.49***	0.08***	0.48***
	(0.05)	(0.17)	(0.04)	(0.17)	(0.02)	(0.17)
I(LTV>=80%)	0.09*	0.01	0.07*	0.02	0.06	-0.03
	(0.05)	(0.18)	(0.04)	(0.18)	(0.04)	(0.19)
I(LTI>=4.5)	-0.01	0.00	0.01	0.00	0.01	-0.03
	(0.05)	(0.16)	(0.04)	(0.16)	(0.03)	(0.16)
I(LTI>=5.5)	0.03	-0.01	-0.02	-0.01	-0.03	-0.02
	(0.05)	(0.20)	(0.04)	(0.20)	(0.04)	(0.20)
I(New Mortg.=1)	0.04	-0.02	0.04	-0.02	0.01	0.03
	(0.05)	(0.17)	(0.04)	(0.16)	(0.02)	(0.17)
Ln(Total Assets)		-0.31***		-0.27***		-0.33***
		(0.04)		(0.04)		(0.04)
Mortgages/TA		-0.03***		-0.03***		-0.03***
		(0.01)		(0.01)		(0.01)
Deposits/TA		0.03***		0.03***		0.03***
		(0.01)		(0.01)		(0.01)
Equity/TA		0.07**		0.05		0.07**
		(0.03)		(0.03)		(0.03)
HHI	0.34	-0.81				
	(0.39)	(0.81)				
HP Growth	-2.08**	-1.62				
	(0.89)	(2.36)				
Number Providers	-0.02***	-0.04**				
	(0.00)	(0.02)				
Unemp. Compl.			-0.44***	0.17		
			(0.08)	(0.22)		
Experience						-0.24***
						(0.08)
Constant	1.01***	0.26	0.36***	-0.45	1.00***	0.27
	(0.09)	(0.77)	(0.06)	(0.82)	(0.03)	(0.74)
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 repeats the estimations of the variance equation with different sets of controls displayed in Table 10 of the main paper, but now probes the robustness of that procedure to using underlying mean equations (also available on request) that are experience year specific. Standard errors in parentheses are robust. * $p<0.1$, ** $p < 0.05$, *** $p<0.01$.

Appendix Table 5: 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.

Appendix Table 6: Geographical Representativeness

	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 (2020), 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.

Appendix Table 7: 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 (2020)

	Our sample	B&M (2020)	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.