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Integrated Intermediation and Fintech Market Power

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Abstract

We document that in the US residential mortgage market, the share of *integrated* intermediaries acting as both originator and servicer has declined dramatically. Exploiting a regulatory change, we show that borrowers with integrated servicers are more likely to refinance, and conditional on refinance, are more likely to be recaptured by their own servicer. Recaptured borrowers pay lower fees relative to other refinancers. This trend is partially offset by a rise in integrated *fintech* originator-servicers, who recapture at higher frequency but at worse terms. We build and calibrate a dynamic structural model to interpret these facts and quantify their impact on equilibrium outcomes. Our model suggests that integreated intermediaries enjoy a marginal cost advantage when refinancing recaptured borrowers, and fully disintegrating them would reduce refinancing frequencies and increase fees. Fintechs use technology to reacquire customers and reduce borrower inertia against refinancing. This endogenously creates market power, which fintechs exploit through higher fees. Despite worse terms ex-post, fintechs increase consumer welfare ex-ante by increasing refinancing frequencies. Taken together, our results highlight the importance of intermediaries' scope in consumer financial outcomes and highlight a novel, quantitatively important application of fintech: customer acquisition.
Keywords: Mortgage market structure, mortgage refinance, fintech, intermediation.

JEL Classification Codes: G2, L5

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A loan origination creates two conceptually distinct assets: the right to the cashflows paid by the borrower—the loan—and the right and obligation to collect payments from the borrower and forward them to the loan's owner in exchange for a fee—the servicing right. In a traditional balance sheet model of banking, origination, servicing, and receiving cashflows are *integrated* within one financial intermediary. However, the modern industrial organization of financial intermediation has seen a striking trend of separating loan origination from loan ownership, e.g., in the context of residential mortgage origination (Buchak et al., 2023) or small business lending (Gopal and Schnabl, 2020). This paper documents and explores the consequences of an additional margin of dis-integration: the increased separation of loan originator and loan servicer.

We study this phenomenon in he context of the US residential mortgage market. As in other contexts, the mortgage servicer occupies an important role in the mortgage intermediation chain. In particular, the servicer maintains a long-term, ongoing relationship with the borrower: The servicer collects monthly payments and forwards them to the mortgage owner. The servicer reminds the borrower when there are late payments. The servicer is potentially responsible for ex-post modifications in the event of delinquency or default. In short, unlike the originator or mortgage owner, the servicer plays an active role in the financial life of the mortgage borrower far after the point of origination. For this reason, it is natural to expect that characteristics of the servicer will have an impact on the borrower's ex-post financial decisions, such as refinancing or default. This paper focuses on the the refinancing impliactions of mortgage servicers.

Our paper uncovers two key economic forces that distinguish combined originator-servicers—which we term *integrated* intermediaries—and integrated fintechs from other, dis-integrated financial intermediaries. First, we show that integrated intermediaries possess a cost advantage in refinancing their existing servicing customers. In particular, by virtue of their long-term relationship with the borrower, the servicer already possesses documents, credit information, and access that are key in the origination of a new loan. Second, we find that integrated "fintech"[1] intermediaries appear to be able to use data and customer access for the purposes of more effective customer acquisition in a manner that non-fintech lenders lack the technical expertise to implement. In particular, fintech lenders are able to refinance their "woodhead" servicing customers who would not otherwise be looking to refinance, and can exploit their resulting market power to refinance the borrower at a higher markup.

We first establish these facts in reduced form in three steps. After documenting a secular

[1]We define a "Fintech" intermediary as in Buchak et al. (2018*a*), where a lender is a Fintech if the loan application occurs entirely online and the potential borrower is able to obtain a firm, contractual rate quote without interacting with a human loan officer.

decline in the market share of integrated intermediaries that is partially offset by a rise in integrated fintech intermediaries, we provide identified evidence that integrated intermediaries lead to more refinancing using a regulatory shock to the capital treatment of mortgage servicing rights on bank balance sheets. Next, using a novel forward-merged data set that allows us to match mortgage originations to future refinances of those same mortgages, we show that refinances originated by the existing servicer are executed with lower fees. This suggests that these lenders possess a marginal cost advantage when refinancing their own customers. We find, however, that fintech intermediaries charge significantly higher fees and refinance their servicing customers sooner and at lower rate benefit to the borrower, suggesting that they are targeting borrowers who would not otherwise be attempting to refinance and charging markups when doing so. Finally, we rule out that our results are driven by alternate mechanisms, such as one intermediary type possessing superior underwriting skills.

After establishing these facts in reduced form, we build and calibrate a structural model that allows us to quantify the size of these forces and consider equilibrium counterfactuals where originators and servicers are fully dis-integrated or where fintech never entered. We find that fully dis-integrating the servicing market would decrease the annual rate of mortgage refinance by roughly 10% and increase prices by roughly 5%. This is primarily driven by the loss of the marginal cost advantage in loan production. The implication from this counterfactual is that the rapid dis-integration of the servicing market was likely responsible for a reduction in the number of borrowers who refinanced their mortgages while rates declined between 2010 and 2022. Additionally, we find that the customer acquisition aspect of financial technology has had a large quantitative impact on mortgage refinance propensities and costs. Fintech customer acquisition ability increased the annual rate of mortgage refinancing by roughly 25% relative to the baseline. It did so by overcoming woodheaded borrower inertia and splitting the resulting surplus by increasing fees by roughly 5%.

Our paper begins by documenting two new empirical trends. First, we document that the share of agency mortgages where the originator is also the servicer—a structure of intermediation we term *integrated*—has fallen sharply since 2010. Figure 1 Panel A shows that integrated intermediation declined from a high of nearly 70% of originations in 2010 to a low of roughly 30% in 2015 before recovering back to 50% in 2020. Second, we document that a significant portion of the subsequent increase in integrated intermediation was driven by the entry of fintech intermediaries, who nearly all operate as integrated originator-servicers. The integrated fintech share of originations rose from zero in 2010 to roughly 12% in 2020. As we show, integreated non-fintech and integrated fintech intermediaries exhibit qualitatively different behavior.

To study this behavior, we first establish two key findings around integrated intermediaries *in general*. We first exploit a change in the regulatory treatment of mortgage servicing assets in 2013: Previously, risk-based capital requirements attached a risk weight of 100% to these assets. In 2013, this risk weight was increased to 250%.[2] This change, as documented in Mayock and Shi (2022), induced many banks (but not non-banks) to sell their mortgage servicing assets. Thus, when considering mortgages originated before 2013, those originated by banks (the treatment group) are less likely to be serviced by an intermediary who is also a mortgage originator than are those originated by non-banks (the control group) following the policy. A difference-in-difference analysis shows that after the risk weight changes, the treated mortgages are significantly less likely to refinance than the control mortgages. No such effect exists among ex-ante bank-serviced mortgages where the servicer at origination was not the originator, ruling out that this effect is merely driven by the shifting of servicing assets from banks to non-banks. This analysis thus provides direct evidence that mortgages serviced by an originator are more likely to refinance than other mortgages.

After showing that whether the servicer is integrated or not impacts the quantity of refinancing, we next condition on refinancing and ask whether mortgages refinanced by the servicer, *recaptured refinances*, differ from those refinanced by a third party. This analysis requires linking the first origination, which provides the identity of the servicer, to the subsequent refinancing mortgage, which provides the identity of the subsequent originator, as well as the new interest rate, timing, and fees. To do this, we undertake a merge, which to our knowledge is novel in the literature, of merged GSE/HMDA originations with forward-matched HMDA originations. With this data, we first confirm the own-servicer refinancing channel described above by directly showing that these refinancing borrowers tend to refinance with their own servicer in particular. In terms of pricing, we next show that recaptured refinances have roughly a $150 lower fee, or 7 basis points as a fraction of the principal. This suggests that refinancing an existing customer has a lower marginal cost as compared to an outsider and that some of these marginal cost savings are passed on to the borrower.

We next show that integrated *fintech* intermediaries in particular appear to possess an advantage in customer acquisition gives them access to otherwise uncontested refinancing customers. With our forward-matched refinancing dataset, we first document that fintech intermediaries focus on recapturing their own servicing customers. Next, we use merged HMDA application data to study borrower search and shopping behavior around refinancing. We find that fintech customers exert significantly less effort in searching and shopping as compared to other lenders' customers: Fintech customers have 10% fewer refinance applications to other competing lenders than non-fintech customers, and customers who receive

[2]Given a capital requirement of 6%, this change means that having $1 worth of mortgage servicing rights went from requiring $0.06 inequity financing to $0.15 in equity financing.

fintech loan offers are nearly 50% less likely to reject the offer. In consequence, fintech lenders face less effective competition and offer their borrowers significantly worse loan terms. Fintech recaptures occur roughly one year earlier in the life of the loan, offer a 20 basis point smaller rate improvement to the borrower, and have a $300 higher fee, or roughly 17 basis points as a fraction of the principal.

Motivated by these facts, we build and calibrate a quantitative structural model of mortgage refinancing and servicing. We do this for three reasons: First, the mortgage refinancing decision is a complicated dynamic problem and in particular is model dependent. Formalizing the refinancing decision into a structural model allows us to properly account for the dynamic relationships of all agents involved and in particular to discuss notions of welfare and optimal refinancing, which is not possible with the reduced form approach. Second, we use the model to back out the key economic forces we identified above—marginal cost advantage and customer acquisition advantage—and to discuss the quantitative relevance of both of them. Third, we use the model to examine the equilibrium price and quantity impact of several policy counterfactuals, such as the impact of further servicer dis-integration or fintech entry.

Our model features a long-lived borrower with a 30-year fixed rate mortgage. As interest rates evolve stochastically, the borrower may want to refinance her mortgage into a lower rate. Consistent with a wealth of empirical literature, the borrower faces significant inertia when refinancing her mortgage, which we operationalize as a fixed cost she must pay in order to obtain mortgage offers. If she decides to refinance her mortgage, she receives offers from imperfectly competitive lenders. To match the empirical facts, we model the lender price as an origination fee that is a markup over their marginal cost of originating the mortgage. If she accepts the offer from an integrated intermediary, a servicing relationship is formed between her and the intermediary. This relationship intermediary then possesses a marginal cost advantage in subsequent refinances to the same borrower.

In the empirical results, we showed that loan characteristics for recaptured refinancing by fintech lenders is different from other integrated lenders. We therefore introduce into the model an integrated fintech lender who, in addition to possessing the same marginal cost advantage in originating loans to its servicing customers, possesses a customer acquisition technology that applies to its servicing customers. We operationalize this by allowing borrowers with fintech servicers to receive a refinancing offer *before* soliciting offers from other lenders at a significantly lower inertia cost. We interpret this as thet fintech lender exploiting servicer customer data to make targeted refinance offers that allow the borrower to partially avoid the mental cost of seeking offers. While seemingly simple, legacy lenders have long struggled to implement similar systems.[3] This targeted offer gives the fintech lender additional market power over other offers, allowing the lender to endogenously set higher markups.

We calibrate the model's parameters chiefly through the simulated method of moments (SMM). The key parameters underlying our mechanisms are (1) the marginal costs of originating loans for both insider and outsider originators, (2) the mental cost associated with obtaining refinance offers, and (3) the reduction in mental cost from refinancing through the fintech's targeted offer. We calibrate these parameters in an over-identified SMM by matching model-predicted moments to those detailed in the reduced form section of the paper. In particular, we utilize the overall level of fees, the changes in fees for fintech and non-fintech integrated lenders, the overall refinance rate, and intermediary market shares. Despite targeting seven moments with four parameters, our model comes reasonably close in matching these key moments in the data.

With the calibrated model, we first explore the economic magnitudes of our two channels. We find that the marginal cost advantage of an originator refinancing its own servicing customers is roughly $250, or roughly 14% of the overall origination cost. Given the observed fee differences, this number suggests that integrated originators realize this marginal cost advantage and pass only some on to borrowers. This cost is not fully passed through because only the relationship intermediary possesses the lending advantage. Further, we find that the fintech customer acquisition technology reduces the mental cost of refinancing by roughly $1,588. The value of this reduction is high, but the fintech captures only some of it through higher fees because it must still compete with both the outside option of other refinance offers and also its own targeted offers in the following period.

We next consider two counterfactuals. We first examine how refinancing quantities and prices would change following full dis-integration of the market. We find that by turning off the marginal cost advantage, the quantity of refinances drops by roughly 10% relative to the baseline and fees increase by roughly 5% relative to the baseline. These quantities show that even though the marginal cost saving of $250 is relatively modest, it has large quantitative implications for refinancing. We next examine a counterfactual world with no fintech targeted offers. Without fintech customer acquisition technology, refinance quantities

[3]Legacy lenders' desires and difficulties in acquiring customers is perhaps best exemplified by a fraud in which JPMorgan Chase paid $175m to acquire student borrower data that was later found to be wholly fabricated. https://www.nytimes.com/2023/01/21/business/jpmorgan-chase-charlie-javice-fraud.html. More generally, many commentators have observed the difficulties banks face in even simple technological innovation. Documented reasons include, e.g., a heightened concern over the risk of upgrading legacy systems. https://www2.deloitte.com/us/en/pages/financial-services/articles/modernizing-legacy-systems-in-banking.html. Third-party apps providing such services to banks and non-fintech lenders, e.g., Blend (https://blend.com/company/about/) came online only in the 2020s.

drop by roughly 25% and prices fall by roughly 5%. Quantities fall because there are many borrowers on the extensive margin of refinancing who would not refinance without the lower mental-cost fintech option. Prices fall because without these targeted offers, there are fewer high-markup fintech refinances in equilibrium. This final result highlights that while the financial technology is used to create and exploit market power, on net this has positive welfare benefits relative to a world where there are fewer people refinancing.

Our paper has several important implications. First, we show that the industrial organization of the servicing market has large quantitative consequences for policy-relevant ex-post borrower outcomes like mortgage refinancing. Because it is the largest consumer finance market in the United States, the refinancing of fixed rate residential mortgages has large direct welfare implications for households and for the passthrough of monetary policy, as well as having pricing implications for the RMBS secondary markets. Di Maggio et al. (2017) showed the effect of mortgage interest rates on other household consumption decisions using adjustable rate mortgages. Our paper highlights that institutional or regulatory changes that impact servicing are likely to have spillover effects into the macroeconomy. Second, our paper highlights important aspects around the contract design of mortgages and mortgage servicing rights. For example, contract provisions that restrict which parties are allowed to refinance mortgages would likely have large quantitative impacts on refinancing propensities.

Finally, our paper emphasizes a key role for financial technology beyond the most commonly cited application: underwriting. For institutional reasons, our setting largely takes the underwriting implications of fintech off the table, and yet, fintech lenders have a large and growing market share. Instead, our paper highlights a customer acquisition application of fintech, where data allows the fintech to source otherwise uncontested customers. By sourcing these underserved customers, fintechs in our setting are able to both bring in customers on the extensive margin and charge them higher markups for the services they provide. An important takeaway from our paper is that in the largest consumer finance setting, the chief application of fintech is a marketing application, not an underwriting application.

Related Literature

Recent changes in the composition of institutions in the financial sector have prompted increased interest in the effect of intermediaries. In the mortgage market, Buchak et al. (2018*a*) and Fuster et al. (2022) study the role of shadow banks and fintech lenders, and Fuster, Lo and Willen (2017) and Bhutta, Fuster and Hizmo (2020) study the impact of intermediation on mortgage interest rates. A related set of papers following the financial crisis of 2008 focused on how institutions and market structure impacted household outcomes. For example, Keys et al. (2010) and Purnanandam (2011) study the originate-to-distribute market. We contribute a brand new intermediary type to this discussion. We define integrated lenders who have a close, existing relationship with borrowers through their servicing role.

A related strand of literature studies so-called "Fintech" intermediaries that harness technology in some way to effect lending and other aspects of intermediation. Berg, Fuster and Puri (2022) provides a useful survey of the recent developments in analyzing fintech lenders in a number of consumer finance markets. Fuster et al. (2022) and Buchak et al. (2018*a*) are two such examples in the mortgage market. Broadly, the fintech literature tends to focus on these intermediaries mustering new data or models to better underwrite or otherwise value underlying assets. See, e.g., Di Maggio and Yao (2019), Buchak et al. (2020). Babina, Buchak and Gornall (2022) highlight additional applications such as product improvement. Our contribution to this literature is to introduce and identify a novel fintech mechanism, namely, their ability to mobilize data in order to acquire customers and market power.

Our paper also draws on recent advances in using structural models to study industrial organization in household finance applications. For example, Buchak et al. (2018*b*), Egan, Hortaçsu and Matvos (2008), and Egan, Lewellen and Sunderam (2022). Allen, Clark and Houde (2019) structurally estimates the impact of search frictions in the Canadian mortgage market. Matteo (2020) analyzes the impact of bank regulation on the UK residential mortgage market. Our paper builds a dynamic, structural model of borrower refinancing which incorporates a marginal cost advantage and superior matching ability for a specific set of lenders corresponding to fintech and integrated institutions.

In the mortgage market, our paper relates to important papers about the structure of mortgage origination. Many of these papers were a response to the subprime mortgage crisis and highlight the importance of intermediaries and market structure in household finance. For example, see Mian and Sufi (2009), Acharya et al. (2011), and Elenev, Landvoigt and Van Nieuwerburgh (2016). In the mortgage space, our paper also contributes to an ongoing discussion regarding the perplexingly low rates of refinancing in the market. There are several potential causes to this rigidity. There can be real or behavioral costs (Andersen et al., 2020), lack of financial sophistication (Jørring, 2020), or matching frictions (Agarwal et al., 2020) which render borrowers inert. Other papers documenting refinancing rates and comparing them to models of refinancing include Keys, Pope and Pope (2016) and Agarwal, Rosen and Yao (2016). Our paper considers the role of integrated and fintech lenders in alleviating the matching frictions which may lead to low rates of refinancing.

More broadly, our paper is related to a line of literature around search costs, competition, and customer acquisition technology. In addition to the aforementioned Allen, Clark and Houde (2019), applications of search to mortgage markets include Agarwal et al. (2020) and Gurun, Matvos and Seru (2016). Egan (2019) studies costly search in the context of consumer bond investments. We also add to a broad literature on competition in consumer finance. In the mortgage space, Scharfstein and Sunderam (2016) and Buchak and Jørring (2021) study the effect of competition on interest rates and fees, respectively. Yannelis and Zhang (2021) studies competition in a different setting, the market for auto-loans, and Jiang et al. (2023) study the role of technology in mortgage origination. In our setting, fintech lenders can alleviate some of the search costs associated with refinancing. If they can target borrowers who have high search thresholds, they can capture a portion of the market and accumulate market power.

Finally, our paper has implications for monetary policy transmission. Related papers which consider how intermediary types can influence monetary policy transmission include Drechsler, Savov and Schnabl (2017), Scharfstein and Sunderam (2016) and Xiao (2020). The intermediary mechanisms studied in this paper has the potential to imapct the efficient pass-through of monetary policy. Borrowers who don't refinance when interest rates are low can dampen the monetary policy effect.

Our paper proceeds as follows. In Section 1 we describe the institutional setting and data. In Section 3 we document empirical facts motivating our paper. In Section 4 we describe the model. In Section 5 we show estimation results and counterfactuals from the model. Section 6 provides a brief discussion of our results and concludes.

1 Data and Institutional Details

We focus on the agency-backed single-family mortgage market. In 2020, agency-backed mortgages comprised approximately 60% of mortgage originations and 72% of refinancings. The overwhelming majority of these loans are 30-year fully amortizing fixed rate mortgages that are prepayable at no cost. The pre-payment feature means that borrowers can benefit from refinancing their mortgage into a lower rate if prevailing mortgage rates fall.

"Agency-backed" loans are originated and sold to the Fannie Mae or Freddie Mac (the GSEs). The GSEs then pool these loans into securities that are tradeable on the secondary market. In exchange for a GSE-set insurance fee, often referred to as a "g-fee," the GSEs guarantee the payments to the mortgage pool against delinquency and default. Importantly for our setting, as a result of these guarantees, originators and mortgage holders bear essentially no credit risk from borrower delinquency and default. However, mortgage holders still face interest rate risk arising from (1) standard duration risk, where the present value of long-dated cashflows declines as rates rise, and (2) prepayment risk, where borrowers may refinance into a lower rate and prepay their existing mortgage, thus cutting the life of the mortgage short.

In this paper, we study two parts of the mortgage life-cycle: servicing and refinancing. A mortgage origination creates an auxiliary asset called a mortgage servicing right ("MSR"). This servicing right gives its owner the right and obligation to act as the mortgage's servicer. Servicers interact with borrowers on behalf of the owner of the mortgage, which in our case are the GSEs and owners of the securitized mortgage pools. Servicers collect monthly payments, ensure the loan is properly insured, and handle delinquencies. In exchange, the MSR owner collects a fee, typically a percentage of the monthly payments collected by the servicer. The serving fee is set, essentially by statute, by the GSEs. While lenders can and often do have mortgage servicing businesses and service their own loans, MSRs can be sold at origination to another institution to conduct the actual servicing of a loan. Thus, while related, the mortgage itself and the MSR are conceptually separate assets owned and managed by potentially different parties. Finally, while servicing rights occasionally trade in a secondary market post origination, the market is illiquid.

A mortgage refinancing is a prepayment of an existing loan, financed by taking out a new loan with different terms. The proceeds from the new loan are used to pay down the remaining principal of the existing mortgage, and because the mortgages in our setting have a prepayment option, this terminates all rights and obligations of the initial mortgage. Mortgages are typically refinanced either to obtain better terms, e.g., a lower rate or longer maturity, or to increase leverage on the underlying asset in order to extract equity (a so-called "cash-out" refinance). In this paper we focus only on the former. The contractual design of agency mortgages dictates that mortgages can be prepaid at no cost, but there are, of course, costs associated with taking out the new loan. For example, the cost of a loan officer or appraisal, or simply a markup that the new lender charges at origination. Importantly, because the refinancing loan is a new mortgage, the borrower is not limited to their existing lender and can choose to refinance with any lender.

1.1 Data

We draw from two main sources of data, which are common in the literature: The Fannie Mae and Freddie Mac origination and performance data (the "GSE data"), and the Home Mortgage Disclosure Act ("HMDA") origination data.

GSE data: Fannie Mae and Freddie Mac provide information on the GSEs' portfolios of 30-year single-family conforming fixed-rate mortgages. This data provides information about the loan at origination, including the names of the lender and servicer at origination, the interest rate, the term, and the principal balance. The origination dataset includes all new loans; including refinancing loans. The monthly performance updates provide information on the loans delinquency status, as well as the date at which a loan is terminated. This can occur if a loan is paid off through a prepayment, end of the term, or refinancing.

In order to study comparable mortgages, we follow the literature and restrict our sample to 30-year mortgages originated for purchases of primary residence homes. These loans are fully amortizing and have full documentation. The loan-level origination dataset further provides interest rates, FICO scores, LTVs, and DTIs, as well as loan size, type, purpose, and location. It also identifies the originator that sold the loan to the GSE in cases where the originator had sufficiently high origination market share in the reporting period.

HMDA: HMDA data covers is a mortgage-application-level dataset covering the near universe of U.S. mortgage applications and originations. This data, used extensively in the literature, includes lender identification, application outcome, and loan type, purpose, size, year of origination, and location at the census tract level.

Since 2018, HMDA has further recorded several further variables that are key in our analysis: loan interest rate, non-interest-rate charges (including origination charges, discount points, and lender credits), loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio. Consequently, while our main sample includes loans since 2005, we do several test including these additional variables in the 2018–2021 sample.

Merging procedure: There is no direct crosswalk linking the GSE data to the HMDA data. In addition to the two underlying data sources, we create a new merged dataset that links mortgages to their new, refinanced loan. To create this match, we first take GSE loans to their HMDA counterparts. The match is based on year, zip code, loan amount, loan purpose, occupancy type, and the original lender name. Then, for these matched loans, we take the sample which is exiting through a refinancing in the month that the loan is recorded as leaving the dataset. We forward match to executed refinancings in the HMDA dataset. Importantly, the substantial information regarding borrowers available in the HMDA dataset facilitates this match. Rather than use loan characteristics, we use borrower characteristics (year, census tract, race, ethnicity, loan amount) to match refinancings with their new loans. To summarize, the empirical analysis for this project consists of several datasets: a random sample from GSE-backed origination and monthly performance data, a random sample of HMDA applications, and forward-linked refinanced loans.

2 Motivation

We document two observable trends motivating our focus on *integration* and *fintech lenders*. First, the share of integrated originations has declined significantly since 2010. Second, this has been partially offset by a rise in integrated *fintech* originations beginning in 2012.

2.1 The declining share of integrated originations

We define an *integrated* origination (or integrated loans) to be a mortgage origination where the originator and servicer at origination are the same entity. We will often interchangeably refer to originators or servicers as *integrated*. In principal, an originator could retain the servicing rights for only a proportion of the loans they originate each month, but in practice, lenders tend to retain the vast majority of their servicing rights or sell most of them.[4] Additionally, while integration is defined at origination, MSR owners can sell the servicing rights at a later date. While this is rare except in some special cases (e.g., after the implementation of the MSR capital rule that we discuss below), the upshot of this potential mismeasurement is that our results will tend to overstate the fraction of loans currently integrated and understate the effects of integration.

Figure 1 plots the monthly share of loans that are integrated at origination. The share of integrated originations is roughly 50% at the beginning of our sample in 2002, rises gradually through the financial crisis before hitting a high of roughly 70% in 2009, before declining steadily to a low of 30% in 2015. Starting from 2015, the share of integrated originations again begins to rise, hitting roughly 50% by the end of our sample in 2020. These aggregate trends are only partially coincident with the rise of non-bank ("shadow bank") *originators* in the agency mortgage sector discussed in Buchak et al. (2018*a*). While traditional bank originators are somewhat more likely than shadow bank originators to retain servicing rights, there is significant time-series variation within both types, and as we show in Appendix Table A2, the aggregate shadow bank origination share explains less than 30% of the variation in integrated share.[5]

[4]Figure A1 in the appendix shows the histogram of retained ratios for each lender-month in a sample of FNMA and FHLMC originated loans data. As the figure shows, these shares cluster at 0% and 100%, with little mass in between.

[5]See Appendix Table A2 Panel A for the aggregate time series. In Panel B, we regress aggregate origination share on shadow bank origination share, bank integration share, and shadow bank integration share. We find that shadow bank origination share explains roughly 30% of the variation in integration share, while within-lender-type variation explains roughly 70% of the variation. Hence, while the broad shift to shadow bank originations plays a large role in the aggregate trends highlighted here, it explains far less than half of the variation.

2.2 The rise of integrated fintech originations

We define *fintech* lenders as in Buchak et al. (2018*a*), which broadly captures the idea of utilizing IT in the mortgage origination process. Under this classification, a lender is a fintech lender if the consumer can receive a firm rate quote without human interaction. Figure 1 Panel B plots the share of loans originated by integrated fintech lenders. Fintech lenders largely entered the market around 2013, at which point their market share beings to grow dramatically. At their height in 2019, integrated fintech lenders originated almost 12% of all agency loans.

Critically for our paper, nearly all fintech lenders are integrated. In our sample of agency loans, 88% of fintech originations are integrated, as compared to 50% or less for other non-bank intermediaries. Thus, as fintech lenders gain market share in originations, the aggregate share of integrated originations also rises. As shown in Figure 1 Panel A, the rise of fintech thus partially offsets the steep secular decline in integrated origination highlighted above.

3 Facts about integrated intermediaries

Having established the decline in integrated lenders and the rise of integrated fintech lenders, we turn to studying mortgage characteristics related to these intermediary types. We document a set of key facts around (1) integrated intermediaries in general, and (2) fintech integrated intermediaries specifically, which motivate our model in section 4. First, having an integrated servicer causes borrowers to refinance at significantly higher frequencies, with these borrowers often refinancing directly with their servicer. These recaptured borrowers pay significantly lower fees as compared to non-recaptured borrowers. Second, fintech intermediaries focus on recapturing borrowers, their customers are less likely to search for other offers and are more likely to accept fintech offers. On origination, these recaptured fintech borrowers realize a less advantageous rate improvement from refinancing and pay significantly higher fees.

We interpret the evidence at the conclusion of this section. To briefly anticipate our proposed mechanism, our evidence on integrated intermediaries in general suggests that intermediaries possess a marginal cost advantage in refinancing their own servicing customers that they partially pass through as lower fees. With respect to fintech integrated intermediaries, our evidence is consistent with fintechs utilizing their servicing pool to acquire customers who consider few alternatives, thus creating and exploiting market power and charging high markups. While we do not take a stand on the exact source for these advantages, an illustrative example of the former is lenders already possessing identity and credit information about their servicing customers. An illustrative example of the latter is fintech lenders integrating borrower-facing servicing and origination interfaces to reduce consumer cognitive burdens around refinancing. In the model of section 4 we explore this mechanism formally.

3.1 Integrated lenders and borrower recapture

Our first fact in this subsection provides causal evidence that integration of a borrower's servicer and originator increases the borrower's refinancing propensity. We then show that this is likely driven by lenders directly refinancing their own servicing customers, and that these recaptured borrowers pay lower fees to refinance.

3.1.1 Servicing customers of integrated borrowers refinance more frequently

We present causal evidence linking the servicer's status as an originator to borrower refinancing propensity, and show that borrowers with loans from integreated intermediaries are more likely to refinance. We posit a connection between servicer, originator, and borrower refinance for several reasons. First, an originator may possess a cost advantage in underwriting loans to its own servicing customers because it already possesses borrower information, paperwork, and, importantly, contact information. Servicers are in the best position to know when their servicing customers would most benefit from a refinance, and can supply their information to their affiliated loan-origination division, thus obviating customer acquisition frictions. Third, incentives for refinancing are most aligned when the servicer does the refinancing. When executed with an outside originator, the refinancing means the servicer would lose future servicing income. For an affiliated originator, refinancing the loan eliminates the old servicing right but creates a new servicing right that immediately flows back to the servicer. Thus integrated servicers have an incentive to encourage their customers to refinance, so long as they refinance with the affiliated originator. Finally, customers have a slight preference for their existing servicers with whom they already have a relationship. In a recent U.S. Mortgage Servicer Satisfaction Study survey,[6] customers were more likely to reconsider an originator in the future if that originator had retained the servicing rights.

To identify this channel, we exploit a regulatory change around the capital treatment of mortgage servicing rights (MSRs) that impacted banks but not non-banks. In particular, the Basel III framework, approved in 2013, increased regulatory capital weights on MSRs from 100 to 250 percent. That is, given a 6% capital requirement, a bank pre-reform was required to finance an MSR asset with 6% equity. Following the reform, a bank was required

[6] https://www.housingwire.com/articles/how-retaining-servicing-provides-a-competitive-advantage/

to finance the MSR with 15% equity. In consequence, the reform made holding MSR assets on balance sheet significantly more expensive for depository institutions, and as shown in Mayock and Shi (2022), depository institutions sold off these assets in large numbers in early 2013.

This regulatory shock provides a natural experiment we use to evaluate the importance of the servicer-originator connection in mortgage refinancing. We consider all agency mortgages originated prior to 2013 where the originator retained the servicing rights. Our treatment group consists of all mortgages initially serviced (and thus originated) by a traditional bank, and our control group consists of all mortgages initially serviced (and thus originated) by non-banks. At origination, having retained the servicing rights, both groups are on equal footing with respect to refinancing their servicing customers. However, following the approval of the more onerous MSR capital rule in 2013, the bank mortgage servicers that comprise the treatment group receive a negative shock in continuing to hold the servicing rights, and are therefore induced to sell these servicing rights to a third party.[7] While the original servicer was by definition also an originator, the third party buyers may or may not be. Thus, mortgages in the treatment group are less likely to be serviced by a mortgage originator after 2013. In contrast, the non-bank servicer-originator mortgages in our control group did not face such a regulatory shock and therefore had no incremental incentive to dispose of their MSRs.[8] Our hypothesis is that refinancing propensity for the treatment group should decline after the capital rule change disintermediates them.

This motivates the following loan-month-level difference-in-difference and dynamic difference-in-difference:

$$Refi_{it} = \beta Post_t \times Bank_i + \gamma_{ct} + \gamma_{cb} + \epsilon_{it} \tag{1}$$

$$Refi_{it} = \sum_{\tau=2011\ Q1}^{2015\ Q4} \beta_\tau I_{t=\tau} \times Bank_i + \gamma_{ct} + \gamma_{cb} + \epsilon_{it} \tag{2}$$

As discussed above, the sample consists of agency mortgages[9] originated between January 2000 and December 2012 where the originator was also the servicer. Here $Refi_{it}$ is a zero-one indicator for whether loan i prepays at time t. β and β_τ are the difference-in-difference and dynamic difference-in-difference coefficients of interest. $Post_t$ is a zero-one indicator for the observation occurring in January 2013 or later. $Bank_i$ is an indicator for whether mortgage

[7]Although these sales are not observable in our data, Mayock and Shi (2022) shows strong evidnece for what is effectively our first stage.

[8]Note that because we cannot directly measure MSR sales, we are estimating an intent to treat effect.

[9]For computationally efficiency we run the experiment on a random 1% sample of loans.

i was originated (and hence serviced at origination) by a depository institution.

In the fixed effects γ_{ct} and γ_{cb}, c refers to interacted binned FICO at origination, binned loan-to-value ("LTV") at origination, 3-digit zip code, and binned current loan size. t refers to time, and b refers to originator type. Thus γ_{ct} are characteristic times time fixed effect and account for time-and-characteristic varying changes in refinance propensities. These fixed effects absorb, for instance, a possible cofounding effect where banks target different customer types from banks who happened to change their refinancing behavior around 2013. γ_{cb} are characteristic times originator type fixed effects and capture originator-and-characteristic time-invariant differences in refinance propensity.

Our mechanism predicts that $\beta < 0$. Following the MSR rule change that caused banks to sell servicing rights, the refi-propensity on bank-originated mortgages decreases because the servicer is less likely to be the originator. Table 2 Panel A shows that this is indeed the case. Column (1) is the baseline specification, with finds that treated loans are roughly 1.6 percentage points less likely to refinance on a given month. Column (2) adds a control for the difference between the loan's original interest rate and prevailing rate (measured in percentage points), and finds little change in the coefficient. Column (3) restricts the sample to those loans that appear clearly in the money: loans with a rate difference of at least 50 basis points. Again, the results are roughly unchanged. These effects are large relative to the mean refinance propensity of roughly 1.7 percent per month.

Next, we show the results of the dynamic difference-in-difference in Figure 2 Panel A. First, the figure shows that bank and non-bank refinance rates are on parallel trends pre-treatment. Upon impact, however, bank-originated mortgages saw a clear downward shift in their refinance propensity.

An alternative mechanism is that non-bank servicers induce a lower rate of refinancing in their servicing customers than bank servicers do, and the Basel III rule shift merely shifts servicing customers from banks to non-banks, thus reducing their refinancing rates. There is a natural placebo test to rule out such a mechanism. In particular, by rerunning our analysis on the sample of loans where the originator was *not* the servicer at origination, but where Basel III nevertheless induced a shift of the servicing rights from banks to non-banks, we can construct a sample of loans that *is not* affected by the severing of the originator-servicer relationship but *is* affected by the bank-to-non-bank shift. If the effect comes merely from the bank or non-bank status of the current servicer, we should observe a similar drop in the refinancing rate among non-integrated mortages previously serviced by banks. In contrast, if the effect comes specifically from severing the originator-servicer relationship, we should see no effect in this sample. Table 2 Panel B shows that there is no effect among the non-integrated loans, which rules out that the effect occurs merely through the shift of servicing rights from banks to non-banks.

3.1.2 Integrated originators recapture their customers

Next, we provide direct evidence that borrowers are more likely to refinance with their servicer if possible, i.e., if the servicer is also an originator. Our empirical approach is to regress a lender's market share among a population of refinancing borrowers on whether the lender is the population's servicer. A positive coefficient in this regression suggests that borrowers are more likely to choose their own servicer when refinancing.

To operationalize this approach, we begin with the forward-matched refinance sample. We aggregate this loan-level data to the lender-market level, where a market is defined as a year × zip × servicer. We then calculate each lender's market share in each market. That is, for a given lender, we measure the share of refinances among borrowers in a given year and zip code sharing a servicer. For each of these markets, the given lender may also be the servicer. We then run the following regression at the lender-market level:

$$Share_{ltzs} = \beta OriginatorIsServicer_{ls} + \gamma_{tzs} + \gamma_{ltz} + \epsilon_{ltzs} \tag{3}$$

$Share_{ltzs}$ is the lender's market share (between 0 and 1) among refinancing borrowers at year t, zip z, with servicer s. $OriginatorIsServicer_{ls}$ is a zero-one indicator for whether lender l is the same entity as servicer s. The coefficient of interest is β. All specifications include market (year × zip × servicer) fixed effects, which absorb market-level demand shocks (and in particular absorb the outside option of not refinancing). We vary the lender fixed effects as described below. Standard errors are clustered at the lender level to allow for correlated shocks within lender, e.g., an unobserved lender quality shock.

Table 3 shows the results. Column (1) includes no lender fixed effects. This column shows that originators have a 21% higher market share among their own servicing customers. It is possible that this is partly driven by unobserved lender quality differences, for instance, that originators who are also servicers are of greater quality than originators who are pure-play originators. Thus, in column (2), we include lender fixed effects, and find a qualitatively similar result of 18.4%. Importantly, including lender fixed effects absorbs differences between banks and shadow banks, and the small change to the estimate suggests that this distinction is not driving our results. Finally, in column (3) we include lender × year × zip fixed effects, which absorbs unobserved time- and location-varying quality differences at the lender level, and find essentially no change in the estimate. Taken together, these estimates suggest a direct connection between servicing and refinancing, where servicing customers are significantly more likely to refinance with their own servicer, when possible.

3.1.3 Recaptured non-fintech borrowers pay lower fees

Having shown a high degree of *recapture*—originators refinancing their servicing customers—our second fact now explores the characteristics and terms of these recaptured refinances in comparison to non-recaptured refinances. For this and the following subsections, we run the following regression in the forward-matched refinance sample at the loan level:

$$Characteristic_i = \sum_J \beta_J Type_i^J + FE + \epsilon_i \tag{4}$$

Here, $Characteristic_i$ is a characteristic of refinancing loan i. We examine three variables pertaining to the timing of the refinance: the years between origination and refinance, the rate improvement, defined as the difference between the old and the new rate (where a higher positive number means a more favorable rate improvement), and the payment improvement, defined as the annual change in mortgage payments (again, a positive number means more favorable terms for the borrower). We further examine three variables pertaining to the cost of the refinance: the dollar origination charges, origination charges as a percentage of loan principal, and breakeven years, defined as the dollar origination charges divided by the annual rate increase. This last variable measures how many years it takes for the payment improvement to equal the cost of refinance; a larger number indicates that it takes longer for the borrower to break even in payment terms in NPV-unadjusted terms.

J indexes characteristics of the refinancing: *Fintech recapture*, *Fintech new borrower*, and *Non-fintech recapture*. Fintech recapture denotes recaptured loans where the original lender was a fintech company. *Fintech new borrower* is a loan refinanced by a fintech lender where the original loan was not a fintech loan. Non-fintech recapture denotes loans recaptured by non-fintech lenders. We reserve discussion of the two fintech categories to section 3.2.3 below when we discuss fintech refinancing characteristics. The omitted category is non-fintech non-recaptures, i.e., a refinance done by a non-fintech lender who is not the borrower's servicer. All specifications include lender type fixed effects (bank vs. non-bank), loan controls (for the refinancied loans), loan controls (for the original loan), and market (year $\times$ three-digit zip) fixed effects. The results are shown in Table 4.

We begin with the non-fintech recapture results in Panel A. This table shows that while non-fintech recaptured refis occur slightly earlier than non-recaptured refis, there is no statistically or economically significant different in terms of interest rate improvement or payment improvement. The rate improvement is only 0.9 basis points higher than the baseline and is not statistically significant. In Appendix A3, we decompose the rate improvement into differences into the rate on the old loan and the rate on the refinance. We find that non-fintech recaptures refinance at rates slightly above baseline, but also refinance loans whose existing rates are slightly above baseline, and on net these cancel out. This 0.9 net basis point difference translates to an insignificant $35 payment difference on average over the course of a year. These magnitudes are small in an absolute sense, and are also small relative to the means of these variables: The mean rate improvement for a refinance is 1.14% (114 basis points) and the mean annual payment improvement is nearly $3,000. The differences for non-fintech recaptures represent a de minimis change relative to this baseline.

Much larger differences emerge when examining fees in Panel B. We find that non-fintech recaptures have $140 lower fees in dollar terms, or 6.5 basis points lower as a fraction of loan principal. These quantities are statistically and economically significant, representing more than a 5% difference relative to baseline. The difference is even more stark in the context of how long a borrower would take to break even after refinancing, as shown in column 3. We find that a borrower refinancing with their non-fintech servicer breaks even 0.29 years, or 3.5 months earlier relative to baseline. Economically, this is a large effect, and is equal to more than 20% of the mean break-even time of roughly 15 months. To summarize, while borrowers refinancing with their own servicer appear to have no advantage in terms of rate improvement, they do enjoy a significant cost advantage in doing so, which at least partially explains previous results showing borrower's higher propensity to refinance with their servicer.

3.2 The special role of integrated fintech lenders

We next study fintech intermediaries in particular. Recall that fintech servicers are overwhelmingly integrated, and a significant portion in the increase in integrated lender market share since 2015 has coincided with the rise of fintech intermediaries. While this suggests that integrating lending and servicing is likely to play a large role in fintechs' intermediation behavior, in this section we show that the consequences of fintechs' integration is qualitatively different from that of other lenders. We first show that even relative to other integrated lenders, fintech lenders recapture at a significantly higher rate. We next show that fintech refinancing applicants are less likely to reject fintech offers or shop elsewhere. Finally, we show that conditional on recapturing, fintech recaptures occur at significantly worse terms for borrowers.

3.2.1 Fintechs recapture at higher frequencies

Using our forward matched refinance sample, we first examine whether fintech refinances are more likely to be recaptures than other lenders' refinances. At the loan level, we run the following regression:

$$Recaptured_i = \beta Fintech_i + FE + \epsilon_i \tag{5}$$

Recaptured is a zero-one indicator for whether the originator is the same entity as the previous servicer. Fintech is a zero-one indicator for whether the originator is a fintech lender, as classifed in Buchak et al. (2018*a*). We include lender type, borrower new loan controls (measured for the newly refinanced loan), original borrower controls (measured with the original loan), and market (year times three-digit zip) fixed effects. The results are shown in Table 5.

Columns (1) and (2) use the full sample of forward-matched loans; column (2) includes additional borrower controls. Across both specifications, we find that fintech originations are significantly more likely to be borrower recaptures. While unconditionally, roughly 14% of the refinances in our sample are recaptures, fintech refinances are roughly 12% more likely to be recaptures. This estimate is both statistically and economically significant and represents nearly a 100% greater likelihood of recapturing as compared to the base rate. Columns (3) and (4) limit the sample to only refinances by integrated lenders. We impose this restriction because mechanically, only integrated lenders can recapture servicing customers, and in principle the first two columns could simply have been picking up the fact that fintech lenders tend to be integrated. In this restricted sample, the unconditional recapture rate is 30%, with a fintech refinances having an incremental 20% likelihood of being a recapture.

These results point to the recapture of servicing customers to be an important source of fintech customers. While recaptures constitute only 14% of a typical lender's refinance portfolio, they constitute nearly 30% of a fintech lender's refinance portfolio. We now turn to have the terms on these fintech recaptures differ from other refinances.

3.2.2 Fintech lenders face less competition in refinancing

We next show that fintech lenders appear to operate in a less competitive consumer environment than other lenders. In particular, we show that fintech applicants are less likely to shop for other refinance offers, and that once an offer is made, fintech applicants are more likely to accept it.

Customer Search Intensity and Fintech Lenders : We examine whether borrowers applying for fintech refinances apply to fewer other lenders. We use this as a proxy for the search intensity of borrowers. We link loan applications to each other based on immutable borrower characteristics such as the borrower's location, race, income, and property type to form application "chains." A detailed description of this match process is available in the appendix. At the application chain (index b) level, we run the following regression:

$$Applications_b = \beta Fintech_b + FE + \mathbf{X}_{controls} + \epsilon_b$$

$Applications_b$ is the number of applications for borrower b. This value is one for loans that were origianted on the first try. It also includes denials that were not ultimately successful. $Fintech_b$ is an indicator for whether the set of matched applications includes an application to a fintech lender or alternatively an originated loan with a fintech lender. We run the analysis on a 5% sample of all application chains between 2018 and 2021.

Table 6 reports these results. Column (1) shows that application spells that include fintech applications have fewer applications overall. A similar result holds for spells that include fintech originations shown in Column (2). The result in Column (2) indicates that successful fintech originations were executed with fewer applications. However, Column (1) shows that multiple fintech attempts which were unsuccessful were also rare. Together, fintech lenders are more successful at matching overall. All application spells have, by definition, at least one application, but the mean number of applications is 1.05. To interpret quantities, our measured coefficients, which range from -0.004 to -0.006, represent roughly a 10% increase in the probability of having more than one application.

Fintech Loan Takeup Rates : In a similar vein, we next examine whether, once approved for a loan, fintech borrowers are more likely to actually complete the borrowing process through origination. Using a random sample of all approved HMDA refinance applications between 2018 and 2021 , we run the following regression at the loan application level,

$$Originated_i = \beta Fintech_i + FE + \epsilon_i \qquad (6)$$

$Originated_i$ is a zero-one indicator for whether the approved loan is originated. $Fintech_i$ is a zero-one indicator for whether the lender is a fintech lender. FE is a collection of lender type, binned borrower characteristics, and market fixed effects. The results are shown in

Table 6 Panel B Columns (1) and (2). Column (2), which is the most saturated specification, shows that approved fintech refinance loans have a 2.7% greater likelihood of being accepted, or conversely, a 2.7% lower likelihood of being turned down by the borrower. The overall rate at which borrowers decline lender offers is roughly 5%, so the fintech effect represents more than a 50% decrease versus the baseline value.

We run an additional specification examining a conceptually similar but slightly different outcome. Among all HMDA applications not rejected by the lender, we examine whether the borrower withdraws her application (or turns down an approved loan). Note that in comparison to the previous specification, this specification includes some loans that are withdrawn by the borrower before the lender makes a credit decision. In consequence, the sample is slightly larger. We show these results in Table 6 Panel B Columns (3) and (4). Here, we find that relative to a mean withdrawl rate of 16%, fintech applications are withdrawn 10% less frequently, again representing an economically and statistically significant difference.

3.2.3 Fintech lenders charge high fees to recaptured borrowers

Finally, we return to the analysis based on regression (4) with results shown in Table 4. Recall, Panel A shows differences in the timing of refinance among various refinance types, and Panel B shows differences in fees. Column (1) in Panel A shows that compared to the base group of non-fintech non-recaptures, recaptured fintech refinances occur nearly 0.9 years, or 10.5 months, earlier. This represents a large effect—nearly 30% faster—relative to the typical time between origination and refinance of 2.8 years. Column (2) shows that this faster refinance translates into a much smaller rate improvement, with the realized rate improvement on recaptured fintech loans being roughly 16 basis points smaller than average. Again, this is a large effect—roughly 14% smaller—relative to the mean improvment of 1.14%. In consequence, the realized annual payment improvement is more than $300 lower, or 10% relative to baseline, for fintech recaptures.

The story is quite different when fintechs refinance borrowers who are *not* their servicing customers. Column (1) shows that fintechs refinance new customers only modestly early, roughly 0.20 years faster relative to baseline. Interestingly, these refinances are modestly more advantageous to borrowers than the baseline arms-length non-fintech refinances, realizing a rate improvement that is 6 basis points better for borrowers. This translates to a payment improvement that is roughly $200 greater. In Appendix A3, we decompose the rate improvement into differences into the rate on the old loan and the rate on the refinance. We find that both recaptured and arms-length fintech refinances occur at roughly market rates, but recaptured fintech refinances target borrowers with lower-than-baseline preexisting rates, while arms-length fintech refinances capture borrowers with slightly higher-than-baseline pre-existing rates.

Turning to fees, Panel B shows that both fintech recaptures and fintech new borrowers charge significantly higher fees compared to baseline refinances. Fintechs charge recaptures \$315, or 15 basis points per loan principal more, while the corresponding premia are \$400, 20 basis points, for new customers. These higher fees, combined with the differential payment improvements shown in Panel A, imply that the break-even time for a fintech recapture is nearly one quarter year longer, or 20% greater than the baseline time. Similarly, the break-even time for a fintech new borrower is .14 years longer, or 10% longer than the baseline time.

To summarize the findings in this section, we find that Fintech lenders focus much more on recapturing their servicing customers than other lenders do. These recaptured refinances occur much sooner and realize much smaller rate improvements than similar refinances effected by arms-length, non-fintech lenders. Despite the fact that these recaptures offer smaller economic benefits to customers, fintechs charge significantly higher fees, with the net effect being that it takes much longer for recaptured fintech refis to offer a net benefit to the borrower.

3.3 Discussion and interpretation

We conclude the empirical section with a brief discussion and interpretation of these facts. The market has been shifting away from a model of mostly integrated originator-servicers towards one where these activites occur in different entities. This is partially driven by market share gains in non-bank originators, who are on average less likely to be integrated, but is largely driven by within-lender type shifts. The rise of fintech intermediaries, which are overwhelmingly integrated, somewhat offsets this secular decline in integrated origination-servicing. Our difference-in-difference evidence suggests that there is an important causal connection between servicer integration and refinance rates, driven by lenders directly refinancing their own servicing customers.

Our results highlight two mechanisms for this channel. First, lenders appear to have a cost advantage in refinancing their own servicing customers. The empirical evidence for this mechanism comes through the lower fees paid by recaptured borrowers compared to arms-length borrowers. While we formalize this idea subsequently in our structural model, these lower fees suggest that originators face lower marginal costs which, through competition, are (partially) passed through to borrowers.

Second, fintech lenders in particular appear to attract refinance borrowers who are not considering other offers, and they draw heavily from their pool of servicing customers in order to do so. To contextualize this mechanism, it is important to consider the broader context in which the overall refinancing rate is "low," with a significant portion of this low rate being explained by search costs or other borrower inertia against refinancing.[10] Our results are consistent with fintech lenders being able to partially overcome that intertia for their servicing customers in particular. In doing so, they obtain local market power over these borrowers and exploit it by charging higher fees. The empirical evidence for this mechanism comes from several results. Fintechs' own share of recaptured refinancings is much higher than other lenders'. Their recaptured customers refinance much earlier and at less advantageous rates as compared to other borrowers, suggesting that they are reaching these customers earlier and before they look to refinance on their own. Finally, once recaptured, these fintech borrowers pay much higher fees, suggesting that fintechs are charging a higher markup in response to their market power.

Finally, we discuss and rule out an alternate fintech lending channel, which is better underwriting. Broadly, much of the fintech literature has examined whether fintech uses technology to better screen borrowers. We note first, for institutional reasons, that lenders originating GSE mortgages have little incentive to invest in more predictive underwriting technology for the simple fact that the GSEs guarantee risk on the loans and that the price of these guarantees is set by a simple and pre-determined FICO $\times$ LTV grid. Additionally, in Appendix A.3, we examine whether fintech loans perform better, and find little evidence in support of this mechanism.

Together, the empirical facts point towards two related mechanism. The first is a margianl cost advantage for integrated lenders. The second is a customer acquisition advantage for fintech lenders. We note that these two advantages appear to complement each other for the fintech case. In the model section below, this is a point we study more closely. Before concluding this empirical section, we discuss supporting evidence and mechanism results regarding the fintech lenders.

4 A Model of Mortgage Refinancing and Servicing

Motivated by our empirical results, we develop a dynamic quantitative model of mortgage refinancing featuring various servicers in a central role. Our model provides an economic framework to help understand our reduced form results. We calibrate the model using several empirical moments from our reduced-form analysis in Section 3 in order to offer a quantitatively realistic picture of the market. Our calibrated model offers an interpretable

[10] See Keys, Pope and Pope (2016), Agarwal, Rosen and Yao (2016), and Agarwal et al. (2020). See Appendix A.1 for our own analogous presentation of these facts.

quantification of key economic forces, namely, the implied cost to a borrower of refinancing her mortgage, the marginal cost benefit accruing to an integrated originator-servicer when refinancing its own servicing customers, and the technological advantage in customer acquisition enjoyed by fintech servicers. Finally, we undertake several counterfactuals in Section 5 to explore the quantity and price impact of servicer integration and fintech entry.

4.1 Model setting

We describe the model setting. We begin by detailing the contracts and agents before explaining the model's timeline and agents' decisions.

4.1.1 Contracts and agents

Mortgage contracts: A mortgage contract indexed by (r_0, t, M) has a (refinanceable) fixed rate r_0, years to maturity t, and initial principal balance M. At origination, the time to maturity is T. Mortgages are fully amortizing and payments are fixed over the life of the loan. We define the (constant given the interest rate) period payment as equal to $r_0 \times A(M; T)$. Simplifying notation, we fix M and T and suppress them in the notation, so that a mortgage contract uniquely identified by (r_0, t) has period payment $r_0 \times A$. Upon refinancing to a new rate r, nothing is changed about the loan except that its period payment becomes $r \times A$.

Servicing contracts: Implicitly associated with each mortgage contract is a servicing contract. So long as the mortgage contract exists, the servicing contract pays its owner a fee proportional to the mortgage payment less servicing costs. We denote this net fee, as a fraction of the mortgage payment, as s, so that each period the owner of the servicing contract receives a flow payment of $s \times r_0 \times A$. We take s to be set exogenously by the GSEs. Reflecting our institutional setting, this fee is paid by the GSEs, who are outside of our model.

Borrowers: Borrower i has an existing mortgage contract indexed by (r_0, t) faces a prevailing interest rate r, and has a pre-existing servicing relationship with servicer j. Each period, the borrower makes her mortgage interest payment, $r_0 \times A$, and decides whether to refinance her mortgage. Except in the case where she refinances with her fintech servicer, the borrower must pay a fixed cost c in order to obtain offers from lenders. This fixed cost c represents the cost of time spent and mental effort of deciding whether to refinance and getting offers and captures the "inert" nature of households in refinancing their mortgages. Borrowers discount the future by a factor $\beta < 1$ and exit the model at time $t = 0$, when their loan is paid off.

Intermediaries: Intermediary j originates and services mortgage refinances for borrowers. When originating a mortgage for consumer i, intermediary j charges a fee f_{ij} and pays a marginal cost of origination equal to mc_{ij}. As we discuss shortly, intermediaries possess market power and in equilibrium will earn an origination markup $f_{ij} - mc_{ij} > 0$. When in possession of a servicing contract $\mathcal{S}(r_0, t)$ the intermediary earns the net servicing fee $s \times r_0 \times A$. To simplify the model, we assume that the *mortgage* (the stream of mortgage payments, as opposed to the origination charge or servicing fees) are sold into a competitive secondary market so that originators only earn profits from origination and servicing fees.

There are three types of intermediaries:

1. *Disintegrated* intermediaries, D: the originator is not a servicer. Upon refinancing a mortgage, the disintegrated originator earns the origination markup and sells the servicing contract to a disintegrated servicer at the expected discounted value of the servicing cashflows. There are N_D disintegrated intermediaries.

2. *Integrated non-fintech* intermediaries, I: the originator is also a servicer. Upon refinancing a mortgage, the integrated non-fintech originator retains the servicing contract and collects the servicing cashflows period-by-period. There are N_I integrated intermediaries.

3. *Integrated fintech* intermediaries, F: additionally, the fintech intermediary possesses an advantage in customer acquisition that we detail shortly. There is one fintech intermediary.

Interest rates: The refinance interest rate available to a borrower evolves exogenously as $r' \sim F(r;\theta)$ where r' is next period's interest rate, r is this period's interest rate, and θ parameterize the distribution $F(\cdot)$.

4.1.2 Borrower's timeline

Borrower i and her associated servicer j enter the period with the state variables (r_0, r, t, j), where r_0 is the fixed rate on the mortgage, r is the rate at which the borrower can refinance, t is the years to maturity on the mortgage, and j is the identity of the servicer. At the start of the period, the borrower makes her mortgage payment $r_0 \times A$ and the servicer receives its servicing fee $s \times r_0 \times A$. If $t = 0$, the game ends. Let $\mathcal{B}(r_0, r, t, j)$ denote the borrower's value function and let $\mathcal{S}(r_0, r, t, j)$ denote the servicer's value function. The mortgage matures at $t = 0$, so that $\mathcal{B}(r_0, r, t, j)|_{t<0} = \mathcal{S}(r_0, r, t, j)_{t<0} = 0$

Standard refinance market: For $t > 0$, the borrower now decides whether to begin the refinancing process. Unless she has a fintech servicer, the borrower must pay a cost

c to obtain mortgage offers from intermediaries. For intermediary k's offer to borrower i, borrower i obtains the following utility:

$$u_{ik} = -f_{ik} + \beta E\left[\mathcal{B}(r, r', t-1, k)\right] + \epsilon_{ik} \tag{7}$$

$$u_{i0} = \beta E\left[\mathcal{B}(r_0, r', t-1, j)\right] + \epsilon_{i0} \tag{8}$$

Where u_{i0} represents the outside option of not refinancing after seeing the offers. Intuitively, the cost of refinancing is the fee paid to the intermediary, and the benefit is changing the fixed rate from r_0 to r (as well as changing the servicer from j to k, which may be indirectly beneficial). The outside option is to not pay the fee and keep the status quo mortgage rate and servicer. ϵ_{ik} and ϵ_{i0} are horizontal taste shocks that realize after the borrower chooses to obtain mortgage offers (capturing, e.g., non-price attributes of intermediaries specific to the borrower). We later specialize as type-1 extreme value shocks for computational simplicity.

Among the offers and outside option $k \in \{0, 1, \ldots, N_D + N_I + 1\}$ the borrower chooses that which maximizes her utility. Her decision problem and ex-ante expected utility from choosing among these offers is as follows:

$$Refi_i = \arg\max_k \{u_{ik}\} \tag{9}$$

$$EU[Standard\ Refi_i] = E\left[\max_k \{u_{ik}\}\right] \tag{10}$$

Where the expected value is taken over realizations of the ϵ_{ik}'s.

The borrower only makes this choice if she chooses to obtain offers. In deciding whether to obtain offers, she considers the expected utility from each choice:

$$u_{i,get\ offers} = -c + EU[Standard\ Refi_i] + \epsilon_{i,get\ offers} \tag{11}$$

$$u_{i,no\ offers} = \beta E\left[\mathcal{B}(r_0, r', t-1, j)\right] + \epsilon_{i,no\ offers} \tag{12}$$

c is the cost of obtaining an offer. If she obtains offers, she receives in expectation the value of considering a standard refinance, defined above. If she does not obtain offers, she proceeds in the status quo with her current mortgage rate and servicer. Finally, $\epsilon_{i,get\ offers}$ and $\epsilon_{i,no\ offers}$ are horizontal taste shocks, parameterized again as type-1 extreme value shocks. Her decision problem and ex-ante expected utility from the choice of whether to obtain offers is as follows:

$$Offer_i = \arg\max\{u_{i,get\ offers},\ u_{i,no\ offers}\} \tag{13}$$

$$EU[Offer_i] = E\left[\max\{u_{i,get\ offers},\ u_{i,no\ offers}\}\right] \tag{14}$$

Targeted fintech market: When the borrower's existing lender is a fintech lender, the fintech lender can make a special targeted offer to the borrower before the borrower decides to obtain other offers. The fintech's fee is f_{ij}^f. The advantage of the fintech's targeted offer is that its targeted nature reduces the borrower's mental cost of refinancing her mortgage. In particular, rather than costing her c, refinancing in this manner costs only $c - \Delta c_F$. The borrower's utility from refinancing in the targeted fintech market with the fintech lender j or not is as follows:

$$u_{i,F} = -f_{ij}^f - (c - \Delta c_F) + \beta E\left[\mathcal{B}(r, r', t-1, j)\right] + \epsilon_{ij}^f \tag{15}$$

$$u_{im\sim F} = EU[Offer_i] + \epsilon_{i0}^f \tag{16}$$

That is, if the borrower refinances, she pays the fee, pays the mental refinancing cost, and updates her mortgage rate and servicer. If she does not refinance, she moves on to the decision, defined earlier, of whether or not to obtain broader offers. Note that even if she rejects the fintech's targeted offer at this stage, she can still accept the fintech's offer in the standard refinance market. As before, the borrower's expected utility from this decision, with expectation taken over the type-1 shocks is:

$$EU[Fintech_i] = E\left[\max\{u_{i,F},\ u_{i,\sim F}\}\right] \tag{17}$$

Combining these equations, we are ready to define the borrower's value function in recursive form:

$$\mathcal{B}(r_0, r, t, j) = -r_0 \times A + EU[Fintech_i] \qquad \text{(j is fintech)}$$

$$\mathcal{B}(r_0, r, t, j) = -r_0 \times A + EU[Offer_i] \qquad \text{(j is not fintech)}$$

Observe that $EU[Fintech_i]$ nests $EU[Offer_i]$ and that both nest the discounted continuation value of refinancing or not. The decisions and implicit market shares that arise from the solution to borrower's problem are as follows:

- $p^f(f, r_0, r, t, j)$, the probability that the borrower accepts the targeted fintech offer given the state variables and offered fee.
- $p^o(r_0, r, t, j)$, the probability that the borrower chooses to obtain standard refi offers.
- $p^k(\{f\}, r_0, r, t, j)$, the probability that the borrower accepts intermediary k's offer given the state variables and menu of offered fees by intermediary k and others.

4.1.3 Intermediaries' timeline

Intermediaries follow an analogous timeline. The current servicer has a value function $\mathcal{S}(r_0, r, t, j)$ and at the start of the period collects the servicing fee $s \times r_0 \times A$.

Standard refinance market: If the borrower chooses to get refinance offers in the standard refinance market, lenders compete in differentiated Bertrand competition, simultaneously setting fees. Each intermediary type, (D,I,F) has a different dynamic problem.

Disintegrated intermediary's problem: A disintermediated intermediary maintains no servicing relationship with a refinance origination customer and instead immediately sells the servicing rights. The origination problem for disintermediated intermediary j is as follows:

$$\Pi^D = \max_{f_j} \quad p^j(f_j, f_{-j}, r_0, r, t, j) \left(f_j - mc_O + \beta E\left[\mathcal{S}^D(r, r', t-1, j)\right]\right) \tag{18}$$

Here, $p^j(f_j, f_{-j}, r_0, r, t, j)$ is the (endogenous) probability that the borrower refinances, f_j is the fee, and mc_O is the marginal cost. If the borrower accepts the intermediary's offer, the intermediary receives the fee, pays the marginal origination cost, and sells the servicing relationship at its discounted expected value. That value is given recursively as follows:

$$\begin{aligned}\mathcal{S}^D(r_0, r, t-1, j) &= s \times A \times r_0 \\ &\quad + \left(1 - p^o(r_0, r, t, j) \sum_k p^k(\{f\}, r_0, r, t, k)\right) \beta E\left[\mathcal{S}(r_0, r', t-1, j)\right]\end{aligned} \tag{19}$$

That is, the servicing relationship pays the servicing fee and survives so long as no other intermediaries refinance the borrower. The borrower refinances if she chooses to obtain offers and accepts one of the offers.

Integrated non-fintech's problem: The problem for an integrated non-fintech intermediary j with no prior servicing relationship is as follows:

$$\Pi_O^I = \max_{f_j} \quad p^j(f_j, f_{-j}, r_0, r, t, j)\left(f_j - mc_O + \beta E\left[\mathcal{S}^N(r, r', t-1, j)\right]\right) \tag{20}$$

Here, $p^j(f_j, f_{-j}, r_0, r, t, j)$ is the (endogenous) probability that the borrower refinances, f_j is the fee, and mc_{ij} is the marginal cost. If the borrower accepts the intermediary's offer, the intermediary receives the fee, pays the marginal origination cost, and gains the servicing relationship. The problem for intermediary j with a prior servicing relationship is slightly different:

$$\begin{aligned} \Pi_I^I = \max_{f_j} \quad & p^j(f_j, f_{-j}, r_0, r, t, j)\left(f_j - mc_I + \beta E\left[\mathcal{S}^N(r, r', t-1, j)\right]\right) \\ & + \left(1 - \sum_k p^k(\{f\}, r_0, r, t, k)\right)\beta E\left[\mathcal{S}^N(r_0, r', t-1, j)\right] \end{aligned} \tag{21}$$

In this case, (1) the intermediary possesses a marginal cost advantage in refinancing its own servicing customer, and pays $mc_I < mc_O$. Additionally, the second term incorporates that if the borrower accepts no offers then the status-quo servicer maintains the servicing relationship through the next period. Unlike the disintegrated intermediary, the integrated intermediary with a relationship takes the fact that it may lose its valuable servicing relationship into account when setting prices. The value function for the servicing relationship is given recursively as follows:

$$\begin{aligned} \mathcal{S}^N(r_0, r, t-1, j) = & \; s \times A \times r_0 + p^o(r_0, r, t, j)\Pi_I^I \\ & + \left(1 - p^o(r_0, r, t, j)\right)\beta E\left[\mathcal{S}^N(r_0, r', t-1, j)\right] \end{aligned} \tag{22}$$

That is, the servicing relationship pays the servicing fee. If the borrower chooses to get offers, the intermediary obtains the insider expected profit Pi_I^I, and if the borrower does not choose to get offers, the intermediary continues with the existing servicing relationship through to the next period.

Fintech intermediary's problem: The fintech intermediary's problem in the standard refinance market exactly mirrors that of the integrated non-fintech problem, except that it has a different value function, $\mathcal{S}^F(r_0, r, t, j)$, which we define shortly.

Targeted fintech market: When there is an existing fintech servicing relationship, the fintech lender can make a special targeted offer to the borrower before the borrower decides whether to obtain other offers. In that case, the fintech's problem is as follows:

$$\begin{aligned}\mathcal{S}^F(r_0, r, t, j) &= s \times A \times r_0 \\ &+ \max_f \ p^f(f, r_0, r, t, j)\left(f - mc_I + \beta E\left[\mathcal{S}^F(r, r', t-1, j)\right]\right) \\ &+ (1 - p^f(f, r_0, r, t, j))\left(p^o(r_0, r, t, j)\Pi_I^F + (1 - p^o(r_0, r, t, j))\,\beta E\left[\mathcal{S}^F(r_0, r', t-1, j)\right]\right)\end{aligned} \tag{23}$$

In this case, the intermediary first obtains the service flow. Second, the intermediary sets a fee f. In setting the fee, the intermediary trades off a higher fee versus a lower chance of refinancing the borrower. If the borrower refinances with the fintech, it pays the fee and maintains the servicing relationship. If the borrower does not refinance with the fintech, it still maintains the servicing relationship with the fintech unless she both (1) chooses to obtain offers and (2) accepts one of the non-fintech offers.

Finally, Figure 3 provides a graphical schematic for the model's timeline. The black boxes correspond to the borrower; the red boxes correspond to the intermediary. Borrowers begin each period with a rate, time to maturity, potential refinance rate, and a relationship. Borrowers then pay interest on their loans. If the borrower has a fintech servicer, the borrower can refinance in the targeted fintech refinance market. If no refinance occurs, the borrower can then choose to pay a cost to obtain refinance offers in a monopolistically competitive market. If she refinances, her rate updates and the cycle repeats. If not, she maintains her rate and servicer relationship. Likewise, the servicer's within-period problem tracks that of the borrower where the servicer sets refinance fees to maximize its lifetime expected income.

4.2 Equilibrium

Equilibrium in the model is defined as follows. First, given fees, borrowers make optimal choices over refinancing with the fintech, obtaining offers, and accepting offers if obtained. These choices are summarized in $p^f(f, r_0, r, t, j)$, $p^o(r_0, r, t, j)$, and $p^k(\{f\}, r_0, r, t, j)$.

Second, taking borrower and other intermediaries' behavior as given, intermediaries set optimal fees. These are: $(f_f^F, f_s^F, f_s^{NO}, f_s^{NI}, f_s^D)$, which denote the fintech fee in the targeted fintech market, the fintech fee in the non-targeted market, the non-fintech integrated no-relationship fee, the non-fintech integrated fee relationship fee, and the disintegrated fee. Optimal fees are defined for each point in the state space.

4.3 Model calibration

We calibrate the model using a combination of time-series estimates, institutional parameters or parameters drawn directly from the literature, and the simulated method of moments. In this section, we describe the calibration process. Table 7 Panel A shows the moments we target in the simulated method of moments; Panel B shows the calibrated parameters and the source of the calibration.

Parameters set using institutional details or existing literature: We set the initial loan principal M to be equal to \$250k, which is roughly the median mortgage size during our time period. The modal mortgage in our data set is a 30-year fixed rate loan, and so we set the initial loan length $T = 30$. We set the servicing fee, expressed in an annual percentage of total loan payments, equal to 50 basis points, which is roughly in line with GSE servicing guidelines. Finally, in line with the literature, we set the subjective discount factor $\beta = 0.95$ Table 7 Panel B summarizes these details.

Parameters set with time-series estimates: We calibrate the interest rate process, $r' = F(r, \theta)$ using a simple autoregressive process in levels. In particular, we assume that $r' = \rho r + (1 - \rho)\mu_r + \sigma_r \epsilon$, $\epsilon \sim \prime, \infty$, where ρ is the AR parameter, μ_r is the long-run mean, and σ_r is the volatility of the shocks. We obtain these parameters by regressing the 30-year mortgage interest rate on its one-year lagged value. These estimates are reported in Table 7 Panel B.

Parameters calibrated through SMM: Finally, we have four remaining parameters to calibrate. These are: mc_O, the marginal cost of origination for a non-relationship originator, mc_I, the marginal cost of origination for a relationship originator, c, the implied mental cost for a borrower to obtain refinance offers, and Δc_F, the mental cost advantage of refinancing with a targeted fintech offer. To calibrate these parameters, we use an over-identified simulated method of moments approach. Table 7 Panel A shows the target moments in the data and those that obtain from the calibration.

While the parameters are identified jointly, we provide a brief intuitive discussion highlight what moments are most informative about our model parameters. Marginal costs, mc_O and mc_I are most directly informed by the fees observed in equilibrium in the data. In particular, our model imposes a parametric structure between fees and marginal costs, where observed fees reflect the combination of a markup (reflecting market power) and a markdown (reflecting some intermediaries' willingness to offer lower fees to win valuable future servicing flows). The overall level of fees implies a level of marginal costs, which we find to be roughly \$1,775. Additionally, recall that fees charged by relationship non-fintech originator-servicers are lower by approximately \$150. This difference is informative about the marginal cost differences for outsiders, mc_O, and insiders, mc_I. Our calibration estimates that this difference is roughly \$250, meaning that originators with a servicing relationship possess a cost advantage that they only partially pass through to borrowers.

The mental, or inertia cost c of obtaining refinance offers is identified, to a first order, by the overall frequency of refinance. A higher frequency of refinance implies that borrowers are obtaining offers more often, which in turn implies that c is low. In contrast, a lower frequency of refinance implies that borrowers are obtaining offers more rarely, which in turn implies that c is high. We find that matching the (low) overall share of refinancing implies a high mental cost of roughly \$11k.

Finally, the mental cost advantage for fintech lenders is identified jointly through a number of moments, including the fintech lending share, the fintech markup over non-fintech fees, and the share of fintech refinances that are recaptures as opposed to new clients. Broadly, a higher fintech lending share, a higher fintech markup, and a higher share of fintech recaptures is consistent with a greater fintech mental cost advantage. Our calibration estimates this advantage to be roughly \$1,588. Despite our SMM calibration being overidentified, the model is fairly successful in hitting the target moments in the data.

5 Model Analysis and Counterfactuals

We conclude by discussing key economic forces in the model and running counterfactuals to understand the importance of servicer intermediation and disintermediation and the role of fintech customer acquisition technology.

5.1 Model analysis

We begin by exploring key economic forces in the model and connecting thtem to our reduced form results by examining some of the model's policy functions. These are shown in Figure 4. Policy functions in this model are a four-dimensional object because they depend in (r_0, t, r, j), the current fixed rate, the mortgage's time to maturity, the potential refinance rate, and the identity of the current servicer. To collapse dimensionality, we fix $t = 5$ and $r = 6\%$, that is, when there are five years left until maturity of the mortgage and prevailing interest rates are 6%. In panels (a), (c), and (e), we plot market shares (conditional on refinancing), and in panels (b), (d), and (f), we plot refinance origination fees. In each case, we plot these outcomes versus the refinance rate gap, $r_0 - r$, i.e., the rate improvement a refinancing borrower would obtain. Values to the left represent less improvement; values to the right represent more improvement.

Panels (a) and (b) show shares and fees when the incumbent servicer is a disintegrated servicer—that is, the servicer is unable to refinance the borrower itself. Panel (a) shows that in this case, non-fintech originators have more market share than fintech originators and that these market shares do not vary with the potential rate improvement. Here, non-fintech market share exceeds fintech market share simply because there are many more non-fintech originators than there are fintech originators, and in the case where the fintech intermediary has no special access through being the servicer, fintechs possess no special advantage.

Panel (b) shows fees. Observe that both fintech and non-fintech fees are increasing through the region where refinance becomes beneficial to the borrower, moving from roughly 2.20 to 2.40 as $r_0 - r$ increases from -0.01 to 0.02. Intuitively, as the refinance becomes more beneficial to the borrower, they are willing to pay more for it, and because the market is not perfectly competitive, lenders can charge higher prices as the refinance becomes more valuable to the borrower. Interesting, although the lenders in this scenario have no marginal cost differences, fintech lenders charge slightly lower fees than non-fintech lenders. This is because, as we will see, the fintech-borrower relationship is more valuable than the non-fintech-borrower relationship and so fintechs are willing to charge a lower price upfront in order to have a greater chance of building the relationship.

Panels (c) and (d) show shares and fees when there is a non-fintech integrated servicer with a preexisting servicing relationship, whose policy function is now shown in green. Interestingly, the relationship servicer charges much higher fees when refinancing has a relatively low value, and decreases its fees when refinancing has a relatively high value. These differences reflect (1) the servicer's incentives to maintain the servicing relationship, and (2) the passthrough of its marginal cost advantage. First, when the value of a refinance is low to a borrower, it is very unlikely that the borrower will refinance with *any* lender. Hence, the relationship lender does not need to worry about losing the relationship, and instead can charge a high fee in hopes that in the highly unlikely case that the borrower chooses to refinance, it will earn significant money on the fee.

In contrast, when the value of a refinance is high to the borrower, the relationship servicer dramatically reduces prices. It reduces prices because when refinancing is very valuable to the borrower, the is likely to obtain refinancing offers and refinance. The borrower's more aggressive effort to obtain refinancing offers endogenously increases the level of competition in the lending market, and in order to maintain its valuable servicing relationship, the relationship servicer reduces prices. Due to its marginal cost advantage, it is able to reduce prices far below those of other lenders. This gap between the relationship servicer's rates and rates from others neatly reflects the rate differences shown in Table 4.

Finally, panels (e) and (f) show shares and fees when there is a fintech servicer with a preexisting servicing relationship. In this case, the fintech's ability to send targeted rate offers at a lower cost to the borrower gives the fintech significant market power, particualrly in states of the world where the borrower is unlikely to obtain offers itself. This occurs primarily in the region of the state space where refinancing has a relatively low value. Here, panel (e) shows that the fintech has a significant market share advantage. This is precisely consistent with our findings on borrower terms in Table 4, showing that fintech refinances tend to occur earlier in the loan's life and at less advantageous rate gaps for the borrower.

Panel (f) shows that the fintech lender exploits this market power to charge significant markups. As the value of refinancing increases to just about 0, this market power advantage evaporates as the fintech expects borrowers to begin obtaining outside refinancing offers. The fintech loses market share and partially responds by decreasing prices. Again, these findings are consistent with 4 showing that fintech recaptures have much higher fees than other origination types despite being relatively disadvantagous to borrowers.

Interestingly, as the value of refinancing becomes extremely high—above 2% in terms of rate difference—fintech fees again rise. This occurs because the dynamic value of having a fintech servicer to offer easier refinances makes the fintech offer more desirable to the borrower *even if the original offer is obtained in the standard refinance market*. In other words, in anticipation of easier refinances in the future, borrowers are wiling to pay more for fintech services today.

5.2 Counterfactual I: Intermediation and disintermediation

We now turn to our first counterfactual. Here, we quantify the importance of the originator-servicer integration in the quantities and costs of refinancing by eliminating the marginal cost advantage of the insider-servicer. In other words, we set $mc_I \equiv mc_O$, so that the insider servicer and the outsider servicer are on equal footing in terms of future refinancing costs. We show the results in Figure 5 Panels (a), (c), and (e). In each panel, we again fix $t = 5$ years and $r = 6\%$, and plot outcomes against the rate gap $r_0 - r$. We show the results by the identity of the incumbent servicer—a disintegrated servicer, a fintech servicer, and an incumbent servicer. Panel (a) shows the percentage change in total refinancing compared to the baseline calibration. Panel (c) shows this in absolute, rather than percentage terms, and Panel (e) shows the percentage change in fees.

Panel (a) shows dramatic percentage reductions in the quantity of refinancing: Around a 50 basis point rate gap, the refinancing rate decreases by roughly 7.5% relative to the baseline when the incumbent servicer is a fintech, and by roughly 5% relative to the baseline when the incumbent servicer is a non-fintech integrated servicer. In terms of annual quantities, panel (c) shows that the fraction of the population refinancing declines by roughly 50 and 25 basis points, respectively. Panel (e) shows how this change is mediated through increases in fees of between 2 and 4 percent relative to the baseline. The effect is greater when there is a fintech incumbent because, due to the fintech's advantage in targeting their own servicing customers, fintechs are the most likely to refinance their own servicing customers and thus when own-servicer refinancing costs see a relative increase, fintechs are the most affected.

This counterfactual illustrates that the cost advantage coming from originator-servicer integration leads to an economically meaningful change in the quantity of refinancing activity. Consistent with our reduced form results, eliminating that connection—as many trends such as increased MSR capital requirements have done—likely have lead to economically meaningful reductions in household refinancing.

5.3 Counterfactual II: Fintech customer acquisition technology

Finally, we examine the importance of fintech's ability to use technology to target their servicing customers for refinancing. We run this counterfactual by sending $\Delta c_F \rightarrow -\infty$, effectively making it impossible for the fintech lender to refinance any customers outside of the standard refinance market. The results, presented analogously to the previous counterfactual, are shown in Figure 5 panels (b), (d), and (f).

Panel (b) shows a dramatic percentage reduction in refinance activity relative to the baseline where fintechs are able to target their servicing customers. These changes are particularly stark when refinancing is relatively less valuable. In these cases, it is highly unlikely that borrowers would pay the cost to obtain offers, and hence the fintech lender's targeting is essentially their only chance at refinancing. However, even for positive and significant refinance values, eliminating fintech's customer acquisition technlogy has quantitatively large effects. When the refinance gap is 50 basis points, the percentage of refinances decreases by 32% relative to the baseline, and even when the refinance gap is 1%, the decrease is roughly 25%.

These findings, where the relative impact of fintech is largest among borrowers who benefit the least from refinancing, are largely consistent with our reduced form findings. In particular, our results in Table 5 showed that *overall*, fintech refinancings tended to be recaptures. In Appendix Table A7, we replicate this analysis on subsamples of the borrower population formed by their ex-ante potential rate improvement. We find that fintech refinances with the smallest rate improvements are the most likely to be recaptures, whereas fintech refinances with rate improvements with greater than 2% are not more likely than other refinances to be recaptures.

We next move to absolute changes in refinancing quantities, as shown in Panel (c).

Observe that almost no change in absolute refinancing quantity is detectable when the refinancing gap is less than 50 basis points. This is because refinancing at this place in the state space—through a fintech relationship or not—is so unlikely that absolute changes are vanishingly small. However, as the refinance gap increases to 1% and the overall rate of refinancing increases, the effect of eliminating fintech customer acqusition technology becomes economically meaningful: the annual rate of refinancing decreases by 6% in absolute terms, which, as discussed above, constitutes roughly 25% of all refinancing.

Panel (f) shows the impact on fees. Recall that one effect of the fintech's ability to target customers was to give it significant market power over those customers. Eliminating that ability reduces the fintech's ability to exploit its market power, and so refinancing fees shrink. These results highlight an apparent tradeoff of the fintech's customer acquisition technology: On one hand, the technology appears to give the fintech market power, and it exploits that market power by charging higher fees. However, that market power exists because it is offering borrowers a significantly cheaper way to refinance their mortgages, while still preserving their existing options. Thus, fintech's customer acquisition technology increases the total surplus, and the fintech captures a portion of that surplus through higher markups. Unlike in a standard market power setting, however, the fintech's higher markups are actually accompanied by a quantity increase through offering a more convenient product.

6 Conclusion

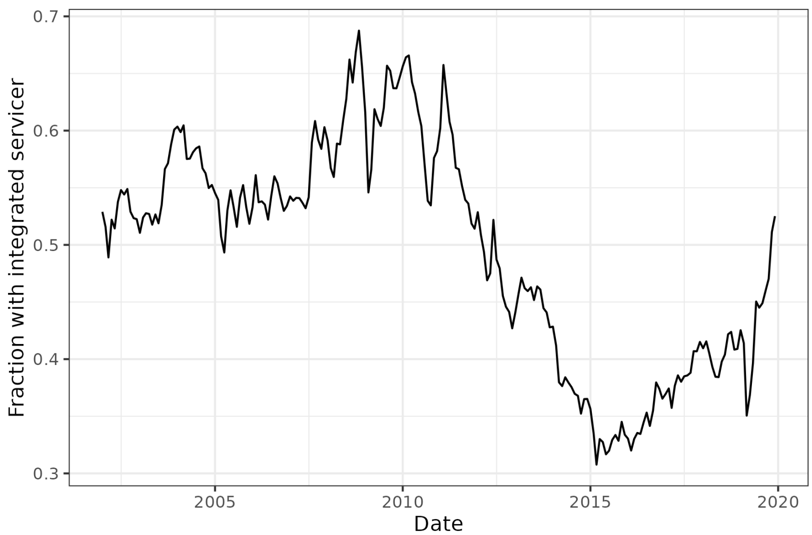
Our paper documented two dramatic changes in the structure of loan servicing in the US residential mortgage market. First, the share of mortgages where the originator is also the servicer has declined dramatically from 70% in 2010 to 30% in 2015, recovering modestly since then. Second, a large share of this recovery was driven by the rise of "Fintech" intermediaries, who both originate and service loans. We explored the consequences for these major shifts for household mortgage refinancing prices and quantities.

We emphasize two economic forces for integrated fintech and non-fintech intermediaries. First, integrated intermediaries have a marginal cost advantage in refinancing their servicing customers. This cost advantage is partially passed through to borrowers in the form of lower fees. Second, fintech intermediaries in particular use data and customer access for more effective customer acquisition. The exploit this unique customer access ability to extract higher markups. We established these facts in reduced form using a change to capital risk weights on mortgage servicing assets that impacted banks and not non banks to show that integrated servicers refinance their servicing portfolio at a higher rate. We also used a novel forward-merged data set to show that refinances originated by the existing servicer are done with lower fees for non-fintechs, and with higher fees and at less advantageous terms for fintechs. We then built and calibrated a quantitative structural model to quantify the importance of these economic forces and run policy counterfactuals. We showed that a fully disintegrated servicing sector would see roughly 10% fewer mortgage refinances at 5% higher prices. Additionally, the fintech customer acquisition channel increases the annual rate of mortgage refinancing by roughly 25% relative to the baseline and an increase in fees by roughly 5% relative to the baseline.

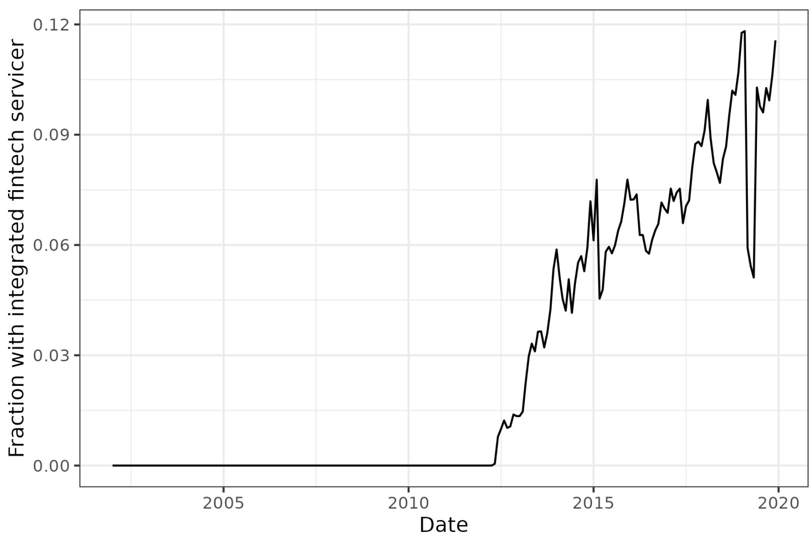
We conclude with several important implications from our paper. First, the industrial organization of the servicing market has large quantitative consequences for policy-relevant ex-post borrower outcomes like mortgage refinancing. Because it is the largest consumer finance market in the United States, the refinancing of fixed rate residential mortgages has large direct welfare implications for households and for the passthrough of monetary policy. Second, Second, there are imporant aspects for the contract design of mortgages and mortgage servicing rights that would have large impacts on refinancing prices and quantities. Finally, we emphasized a novel role of fintech: customer acquisition, as opposed to underwriting. In our setting, fintechs source otherwise uncontested customers and charge higher markups. An important takeaway from our paper is that in the largest consumer finance setting, the chief application of fintech is a marketing application, not an underwriting application.

Figure 1: Mortgage Market Recent Trends

Note: The first panel of the figure plots the monthly share of originated loans where the lender is an integrated lender-servicer. The sample is a random draw from the full set of single-family FNMA and FHLMC loan originations. We identify integrated loans by matching lender and servicer names. Loans where the lender or servicer is too small to be named in the data files are removed. The second panel shows the monthly share originated by integrated fintech lenders. The sample is identifical to panel A but the numerator includes loans that are not only integrated but the lender is identified as a fintech lender using the definition in Buchak et al. (2018*a*).



Panel A: Integrated Origination Share



Panel B: Integrated Fintech Origination Share

Figure 2: Integrated Servicers Refinancing: Event Study

Note: The figure plots the coefficients from the dynamic difference-in-difference test given by

$$Refi_{it} = \sum_{\tau=2011\ Q1}^{2015\ Q4} \beta_\tau I_{t=\tau} \times Bank_i + \gamma_{ct} + \gamma_{cb} + \epsilon_{it}$$

The sample consists of all agency loans originated between January 2000 and Decmeber 2012 with an integrated lender. The dependent variable is an indicator equal to "1″ if the loan exits through a refinancing at time t. The event depicted in the event study is January 2013 when the Basel III framework changed the costs of holding on to MSRs as an asset for bank lenders. Following this implementation, banks were less likely to also be servicers and thus, became unintegrated.

The fixed effects γ_{ct} are interacted, binned FICO at origination, binned LTV, 3-digit zip code, and binned current loan size. γ_{cb} refers to the originator type.

The plot shows a significant decline in the refinancing rates of loans originated by bank lenders following the 2013 change in the MSR capital rule.

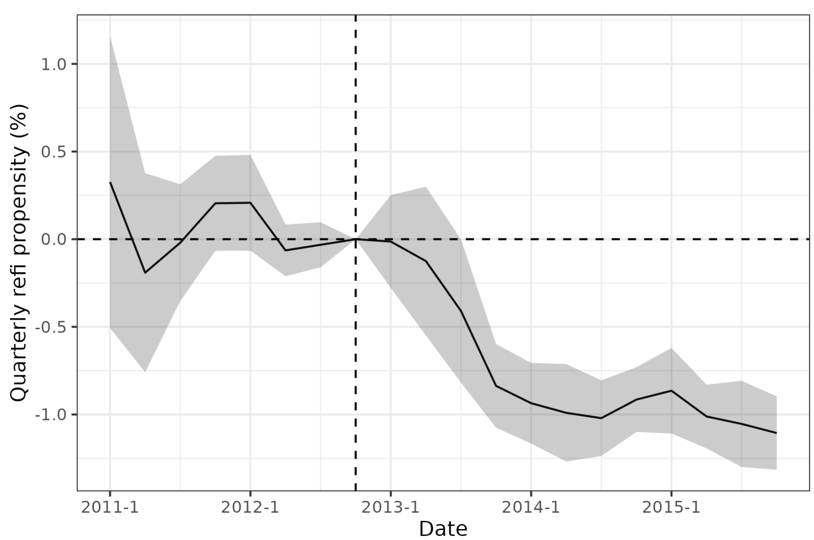


Figure 3: Model timeline

Note: This figure provides a representation of the within-period timeline of the quantitative structural model. The black boxes correspond to the borrower; the red boxes correspond to the intermediary. Borrowers begin each period with a rate, time to maturity, potential refinance rate, and a relationship. Borrowers then pay interest on their loans. If the borrower has a fintech servicer, the borrower can refinance in the targeted fintech refinance market. If no refinance occurs, the borrower can then choose to pay a cost to obtain refinance offers in a monopolistically competitive market. If she refinances, her rate updates and the cycle repeats. If not, she maintains her rate and servicer relationship. Likewise, the servicer's within-period problem tracks that of the borrower where the servicer sets refinance fees to maximize its lifetime expected income.

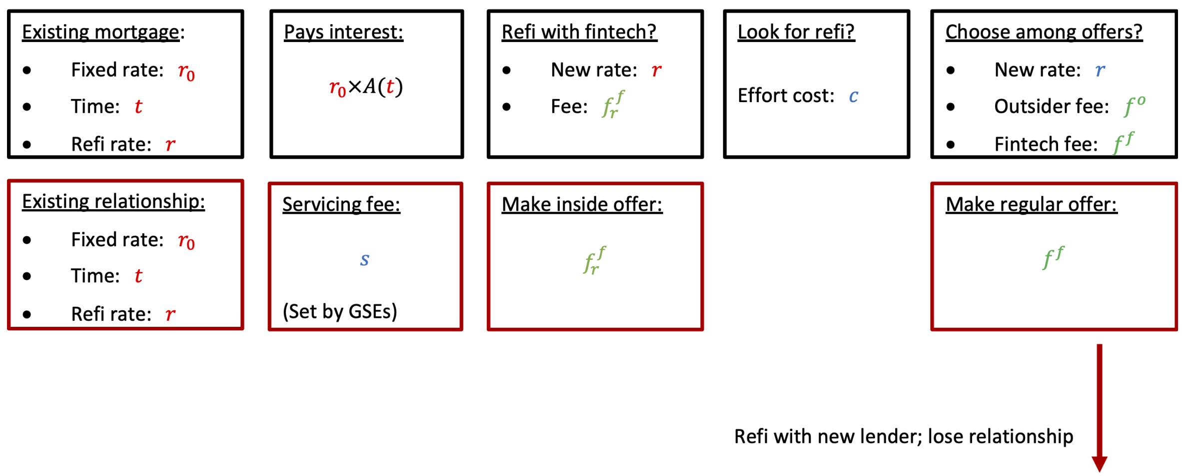
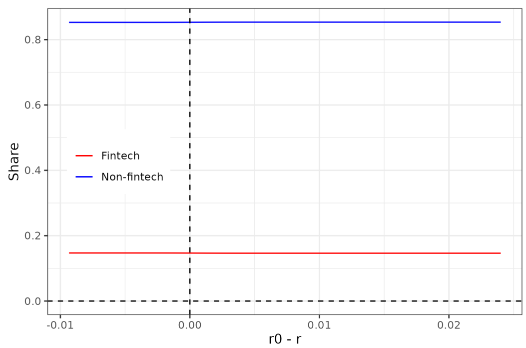
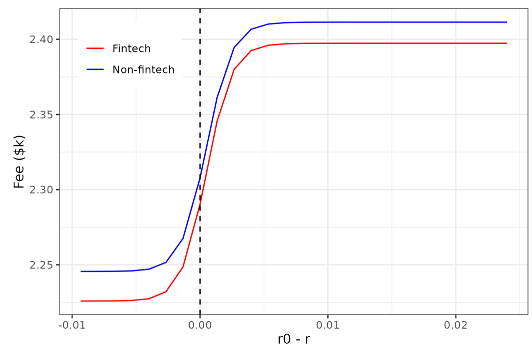


Figure 4: Policy functions

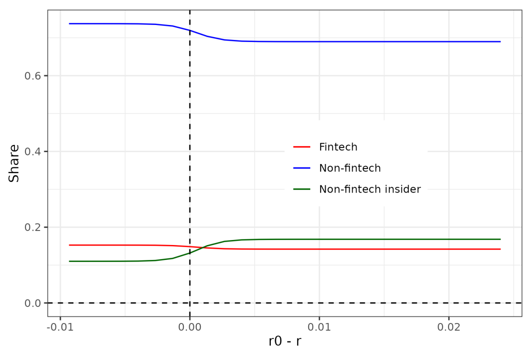
Note: This figure shows originator policy functions from the calibrated structural model. All figures show optimal policies versus the rate gap between the current fixed rate and the rate at which borrowers could refinance for $t = 5$ years remaining and $r = 6\%$. Panels (a), (c), and (e) show origination shares; panels (b), (d), and (f) show fees. Shares are expressed in decimals and fees are expressed in thousands of dollars. Panels (a) and (b); (c) and (d); (e) and (f) show results for when the incumbent servicer is dis-integrated, integrated non-fintech, and fintech, respectively. The red, blue, and green lines are the policy functions of fintechs, non-fintech outsiders, and non-fintech insiders, respectively.



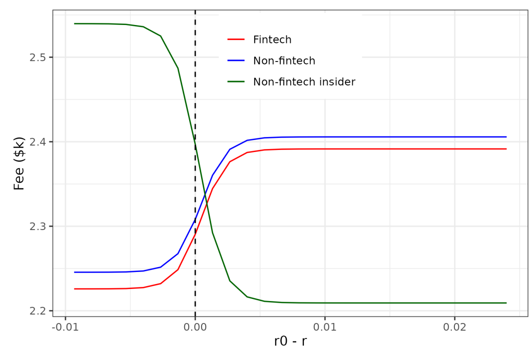
(a) Shares, disintegrated servicer



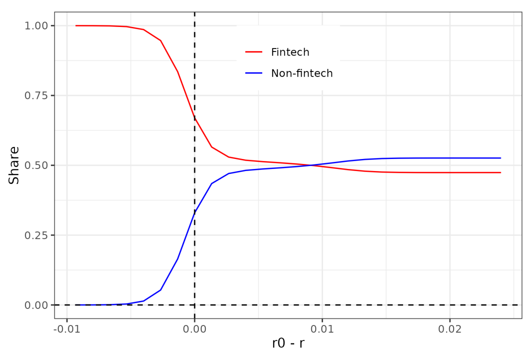
(b) Fees, disintegrated servicer



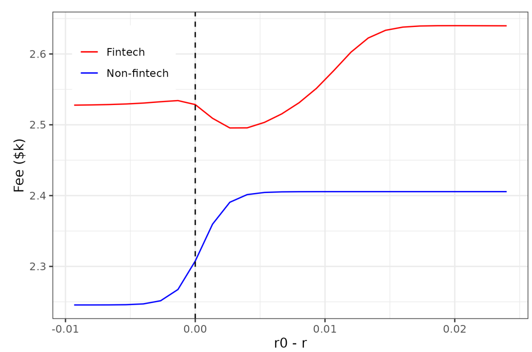
(c) Shares, integrated servicer



(d) Fees, integrated servicer



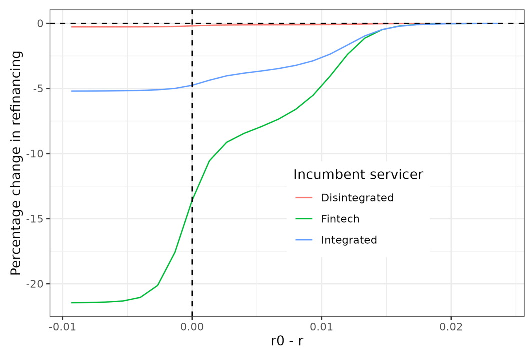
(e) Shares, fintech servicer



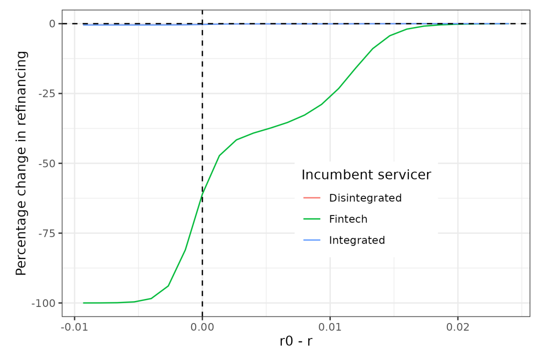
(f) Fees, fintech servicer

Figure 5: Counterfactuals

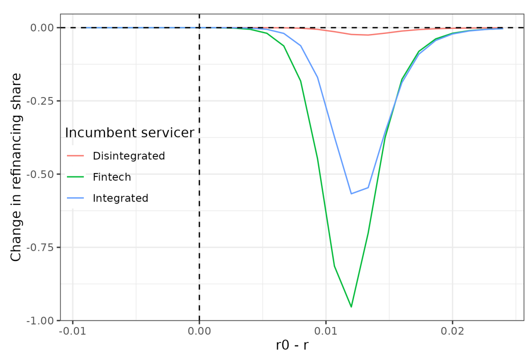
Note: This figure shows counterfactuals from the calibrated structural model. All figures show optimal policies versus the rate gap between the current fixed rate and the rate at which borrowers could refinance for $t = 5$ years remaining and $r = 6\%$. Panels (a), (c), and (e) show the counterfactual that eliminates the marginal cost advantage of insider servicers; Panels (b), (d), and (f) show the counterfactual that eliminates customer access advantage of fintechs. Panels (a) and (b) show changes in refinancing propensities in percentage terms relative to the baseline. Panels (c) and (d) show the same changes in absolute changes. Panels (e) and (f) show changes in refinancing fees in percentage terms relative to the baseline.



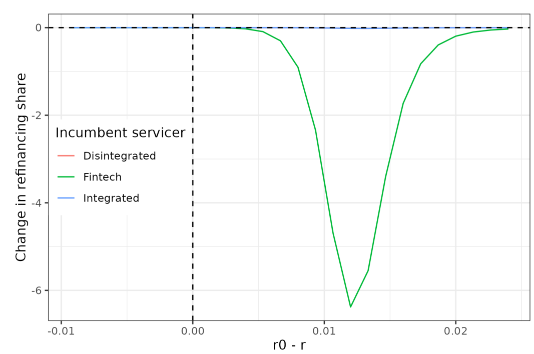
(a) Share percent changes, MC counterfactual



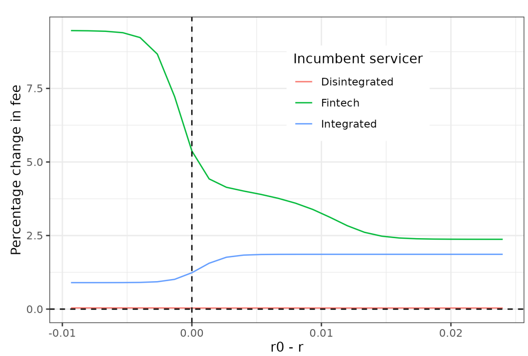
(b) Share percent changes, fintech counterfactual



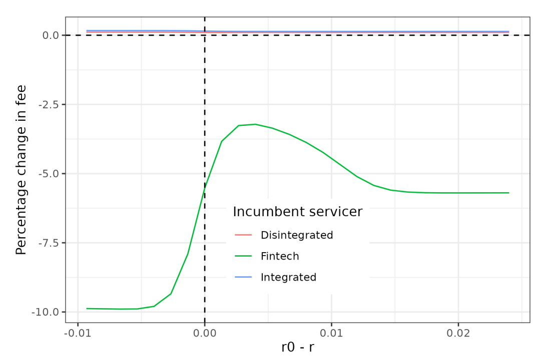
(c) Share absolute changes, MC counterfactual



(d) Share absolute changes, fintech counterfactual



(e) Fee % changes, MC counterfactual



(f) Fee % changes, fintech counterfactual

Table 1: Summary Statistics

Note: Panel A shows summary statistics for the random sample of FNMA and FHLMC loans used in the MSR capital event study shown in table 2. The sample consists of loans at origination and the summary statistics are separated by bank vs. non-bank lenders. Panel B shows summary statistics for the forward-linked refinancing sample. These are FNMA and FHLMC loans exiting through a refinancing which we have forward linked to their new mortgage using HMDA data. The summary statistics show loans originated by fintech lenders as compared to the full set of integrated lender-servicer loans. Note that integrated fintech loans falls under both categories.

Panel A: GSE sample

	N				
Unique Loans	79,593				
Bank Lenders	66,759				
Non-bank Lenders	12,834				
		Mean		Std	
		Bank	Non-bank	Bank	Non-bank
Interest Rate		5.11	4.22	0.96	0.76
Refi		0.02	0.02	0.15	0.15
DTI		33	31	12	10
Loan Amount		200,395	208,114	118,889	128,796
Rate gap		1.21	0.37	1.00	0.82

Panel B: Linked Refinances sample

	N				
Unique Loans	78,484				
Integrated	36,643				
Fintech	20,258				
		Mean		Std	
		Fintech	Integrated	Fintech	Integrated
DTI		35	35	9.32	9.16
Loan Amount		307,764	155,079	151,298	155,079
Refi Amount		289,462	292,152	149,093	154,379
Rate Improvement		1.14	1.06	0.64	0.61

Table 2: Post-MSR capital rule event study

Note: Panel A shows the baseline results from the difference-in-differences MSR capital rule change. The specification is,

$$Refi_{it} = \beta Post_t \times Bank_i + \gamma_{ct} + \gamma_{cb} + \epsilon_{it}$$

$Post_t$ is an indicator for months after January 2013 when the Basel III rule changed the cost to banks of holding MSR assets. The sample consists of a random draw from the FNMA and FHLMC monthly performance dataset and observations are at the loan-month level. The summary statistics for these loans at origination is reported in table 1. The results show the coefficient β for specifications without rate-gap controls in the first column, with rate-gap controls, and in-the-money loans. The rate gap is defined as $r_{old} - r_{prevailing}$. In the money loans are those for whom the rate gap is higher than 50 basis points. Loan controls × servicer are fixed effects interacting bins of borrower FICO scores, debt-to-income ratios, loan-to-value, loan size, and zip codes. Loan controls × date are the same borrower controls interacted with report date instead of servicer. Standard errors, clustered at the report date level, are shown in parentheses. Panel B shows the results for the placebo test which limits the sample to non-integrated originators only.

Panel A: Event study

	Dependent variable:		
	% Refi		
	(1)	(2)	(3)
Post x Bank servicer at origination	-1.635^{***}	-1.504^{***}	-1.557^{***}
	(0.196)	(0.196)	(0.296)
E[Y]	1.69	1.69	1.95
Loan controls x servicer	Y	Y	Y
Loan controls x date	Y	Y	Y
Rate gap control	N	Y	Y
Sample	All	All	ITM
Observations	2,714,576	2,714,576	2,029,899
R^2	0.487	0.488	0.536
Note:	*p<0.1; **p<0.05; ***p<0.01		

Panel B: Placebo (non-integrated originators)

	Dependent variable:		
	% Refi		
	(1)	(2)	(3)
Post x Bank servicer at origination	−0.226	−0.179	0.131
	(0.156)	(0.156)	(0.169)
E[Y]	1.68	1.68	1.90
Loan controls x servicer	Y	Y	Y
Loan controls x date	Y	Y	Y
Rate gap control	N	Y	Y
Sample	All	All	ITM
Observations	3,439,660	3,439,660	2,951,084
R^2	0.718	0.718	0.747
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 3: Borrower recapture and lender market share

Note: This table shows how originator market share varies with whether the lender is the borrower's servicer. Data are constructed from the forward-matched refinance data. Observations are at the lender-market level, where a market is a year × three-digit zip × servicer. The left-hand side variable is market share. *Originator is servicer* is an indicator for whether the lender is the servicer for the current market. All columns include market (year × three-digit zip × servicer) fixed effects. Column (2) includes lender fixed effects. Column (3) includes lender × year × three-digit zip fixed effects. Standard errors, in parentheses, are clustered at the lender level.

	Dependent variable:		
	Originator market share		
	(1)	(2)	(3)
Originator is servicer	0.217***	0.184***	0.186***
	(0.015)	(0.010)	(0.011)
Year × Zip × Servicer (Market) FE	X	X	X
Lender FE		X	
Lender × Year × Zip FE			X
Observations	47,603	47,603	47,603
Adjusted R^2	0.742	0.818	0.793
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 4: Lending Consequences of Recapture

Note: The two panels of this table relate loan characteristics to the refinancing type. The sample is the forward-linked refinance data. We distinguish lender types based on "Fintech recapture" (fintech loans which are recaptured), "Fintech new borrower" (fintech refinancings where the previous lender was different), and "Non-fintech recapture" (recaptured loans where the lender was not a fintech lender). Panel A shows outcomes around the timing of the refinance: *Years to refi*, which is the number of years between origination and refinance, *Rate improvement*, which is $r_{old} - r_{new}$ (in percentage points) between the old rate and the new rate (a positive number means a larger improvement from the borrower's perspective), and *payment improvement*, which is the approximate change in annual payment in dollar terms after the refinance ($New\ Loan\ Amt \times (r_{old} - r_{new})\frac{1}{100}$). Panel B shows outcomes around the cost of the refinance: The fee, both in dollar terms and in percentage points of the loan principal, and *breakeven years*, which is the fee divided by the annual payment improvement. It measures how many years have to pass before the payment improvement exceeds the origination charge. $E[Y]$ is the mean of the left-hand side variable. All columns include lender type (bank versus shadow bank) fixed effects, market fixed effects, fixed effects associated with loan charactersitics of the new refinancing loan, and continuous borrower controls for the loan *at origination of the original loan.* Note that the coefficients of interest are robust to which set (origination or refinancing) borrower controls are used. The new loan fixed effects are interactions of HMDA variables: debt-to-income ratio bins, combined loan-to-value bins, bins of borrower income, and applicant age. Continuous origination controls are debt-to-income, CLTV, original loan size, and original loan term. Finally, market fixed effects are 3-digit zip code × year. Standard errors, clustered at the lender-county level, are shown in parentheses.

Panel A: Timing of refinance

	Dependent variable:		
	Years to refi	Rate improvement	Payment improvement
	(1)	(2)	(3)
Fintech recapture	−0.889***	−0.156***	−322.418***
	(0.053)	(0.017)	(39.105)
Fintech new borrower	−0.197***	0.062***	198.765***
	(0.035)	(0.008)	(19.741)
Non-fintech recapture	−0.690***	0.009	35.544
	(0.043)	(0.012)	(35.286)
E[Y]	2.84	1.14	2987
Lender Type FE	Y	Y	Y
Borrower New Loan FE	Y	Y	Y
Borrower Controls	Y	Y	Y
Market FE	Y	Y	Y
Observations	78,373	78,373	78,373
Adjusted R^2	0.280	0.240	0.403
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel B: Fees on recaptured Loans

	Dependent variable:		
	Fee ($)	Fee (% of principal)	Breakeven years
	(1)	(2)	(3)
Fintech recapture	315.219***	0.154***	0.233***
	(37.847)	(0.015)	(0.040)
Fintech new borrower	401.427***	0.211***	0.142***
	(28.613)	(0.013)	(0.022)
Non-fintech recapture	−140.046***	−0.065***	−0.290***
	(25.303)	(0.009)	(0.022)
E[Y]	2,201	1.05	1.29
Lender Type FE	Y	Y	Y
Borrower New Loan FE	Y	Y	Y
Borrower Controls	Y	Y	Y
Market FE	Y	Y	Y
Observations	78,373	78,373	78,373
Adjusted R^2	0.113	0.350	0.205
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Fintech Borrower Recapture

Note: The table shows results from regressions of recaptured status on a fintech lender indicator. The sample consists of all loans in the forward-linked refinancing dataset. The dependent variable is one if the refinanced loan was recaptured and zero otherwise. The first two columns show results using the full sample while the third and fourth columns show results for the sub-sample of refinanced loans that were originated by integrated lenders. The table indicates whether or not the results include lender type (bank versus shadow bank) fixed effects, market fixed effects, fixed effects associated with loan charactersitics of the new refinancing loan, and continous borrower controls for the loan *at origination of the original loan.* Note that the coefficients of interest are robust to which set (origination or refinancing) borrower controls are used. The new loan fixed effects are interactions of HMDA variables: debt-to-income ratio bins, combined loan-to-value bins, bins of borrower income, and applicant age. Continuous origination controls are debt-to-income, CLTV, original loan size, and original loan term. Finally, market fixed effects are 3-digit zip code × year. Standard errors, clustered at the lender-county level, are shown in parentheses.

Panel A: Fintech and borrower recapture

	Dependent variable:			
	Recaptured refinance			
	(1)	(2)	(3)	(4)
Fintech	0.125***	0.123***	0.207***	0.204***
	(0.010)	(0.010)	(0.014)	(0.014)
Sample	All		Integrated only	
E[Y]	0.14	0.14	0.30	0.30
Lender Type FE	Y	Y	Y	Y
Borrower New Loan FE	Y	Y	Y	Y
Borrower Controls	N	Y	N	Y
Market FE	Y	Y	Y	Y
Observations	78,484	78,373	36,643	36,603
Adjusted R^2	0.086	0.101	0.129	0.133

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Fintech borrower shopping

Note: This table examines the shopping behavior of fintech borrowers. Panel A examines borrower search behavior by regressing the number of mortgage applications in a given application spell on whether the spell includes a fintech search or origination. *Applications* counts the number of searches. *Fintech application* and *Fintech lender* are indicators for whether there is a fintech application or a fintech origination in the spell, respectively. Panel B examines the likelihood that borrowers accepts a loan offer made by a fintech lender as compared to all other lenders. In Columns (1) and (2), the sample is all approved refinance applications in HMDA between 2018 and 2021. A loan is approved if the loan was eventually originated or it was withdrawn by the borrower. The left-hand side variable is a zero-one indicator for whether the approved loan is originated. In Columns (3) and (4), the sample is all refinancing applications. This includes loans that were eventually originated, withdrawn by the borrowers, or any applications that were unsuccessful for any reason including incompleteness. The left-hand side variable is an indicator equal to one if the borrower either withdrew an application before it was complete or did not proceed with the loan after the offer was approved. Standard errors are clustered at the lender-county level. Colums in both panels include, as indicated, lender type fixed effects, borrower controls, continuous borrower controls, and market fixed effects. Lender type is an indicator variable for bank vs. non-bank lenders. Borrower controls are interacted fixed effects of debt-to-income ratios, combined loan-to-value ratios, applicant income, and age. Continuous origination controls are debt-to-income, CLTV, original loan size, and original loan term. Market fixed effects are three-digit zip × year of the HMDA record.

Panel A: Fintech borrower search behavior

	Dependent variable:	
	Applications	
	(1)	(2)
Fintech application	-0.004^{***}	
	(0.001)	
Fintech lender		-0.004^{***}
		(0.001)
E[Y]	1.05	1.05
Lender Type FE	X	X
Borrower Controls	X	X
Market FE	X	X
Observations	1,010,492	1,010,492
Adjusted R^2	0.008	0.008
Note:	*p<0.1; **p<0.05; ***p<0.01	

Panel B: Fintech offer acceptance rates

	Dependent variable:			
	Originated		Borrower withdrawn	
	(1)	(2)	(3)	(4)
Fintech	0.023^{***}	0.027^{***}	-0.074^{***}	-0.102^{***}
	(0.002)	(0.002)	(0.002)	(0.003)
E[Y]	0.95	0.95	0.16	0.16
Lender Type FE	N	Y	N	Y
Borrower Controls	N	Y	N	Y
Market FE	N	Y	N	Y
Observations	94,515	94,515	134,483	134,483
Adjusted R^2	0.002	0.257	0.007	0.446
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Model calibration

Note: This table shows the moments used in the calibration (Panel A) and the calibrated parameters values (Panel B). Panel A shows the moment description, the value of the moment in the data, the value of the moment in the calibration, and their difference. Note that the calibration is significantly overidentified, using seven moments to calibrate four parameters. Panel B shows the parameter values, a brief description, the calibrated value, and the source for the calibration.

Panel A: Targeted Moments

Moment	Data	Model	Difference
Refinance probability	0.203	0.225	0.023
Refinance fee	2.291	2.284	-0.007
Non-fintech recapture Δ price	-0.150	-0.204	-0.054
Fintech recapture Δ price	0.300	0.212	-0.087
Recapture share of fintech	0.310	0.340	0.030
Recapture share of non-fintech	0.140	0.065	-0.074
Fintech share	0.120	0.266	0.146

Panel B: Calibrated Parameters

Parameter	Description	Value	Source
ρ	Rate AR coefficient	0.850	30-year mortgage rate time series
μ_r	Long-term rate mean	0.060	30-year mortgage rate time series
σ_r	Rate shock volatility	0.006	30-year mortgage rate time series
M	Initial loan principal ($\$k$)	250	Median mortgage size
T	Loan length (years)	30	30-year FRM
s	Servicing fee (annual % of principal)	0.0050	GSE policy
β	Subjective discount factor	0.95	Standard assumption
mc_O	Outsider marginal cost	1.775	SMM
mc_I	Insider marginal cost	1.539	SMM
c	Inertia cost ($\$k$)	11.337	SMM
Δc_F	Effective fintech inertia advantage ($\$k$)	1.588	SMM

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A Appendix

A.1 Low rates of mortgage refinancing

We adopt a simple strategy to highlight the low level of refinancing. We begin following a cohort of loans the first time that it is sufficiently "deep in the money" for refinancing: when its current rate r_{old} is more than 50 basis points above the prevailing new origination rate $r_{prevailing,t}$. For example, the January 2019 cohort consists of all loans whose rate exceeds the prevailing rate by 50 basis points for the first time on January 2019. We then ask what fraction of loans in that cohort refinance within three years. We show these refinancing rates in Figure A4 Panel A. This figure shows that for the majority of the sample, the refinancing share is below 10%. That is, even for mortgages that are deeply in-the-money to refinance, only a small fraction actually refinance within a reasonable time frame. Panel B of that same figure shows a different slightly different version of this analysis. For each month, the sample consists of all loans whose interest rates are 50 basis points higher than the prevailing. The y-axis then shows what proportion of those loans actually refinance in that month. If they don't choose to exit, they reappear in the following month as long as their interest rate is still at least 50 basis points above the prevailing. The highest refinancing share achieved in this measure is 30%.

A.2 Fintech Refinance Share

While the discussion above indicated low refinance rates *on average*, we supplement this analysis with results on fintech lenders. Table A5 shows results of a cox proportional hazard model of exits through refinancing on a zero-one fintech indicators. Age is defined as months since origination and a death even is defined as exit through refinancing. Panel A shows the results of the model with borrower controls. The coefficient of 0.064 implies $exp(0.064) = 1.06$ indicating that borrowers with fintech lenders are 6% more likely to refinance. The results in panel A includes borrower controls which are not available in the kaplan-meier survival probability curves shown in panel B. On average, fintech borrowers diverge in their survival likelihood at around 30 months.

A.3 Fintech and borrower delinquency

Here, we rule out an alternate force that might lead fintech lenders to behave differently: different underwriting ability. The idea, popular in the literature, is that fintechs possess a technological advantage in underwriting and are thus better able to predict borrower default. We note first, for institutional reasons, that lenders originating GSE mortgages have little incentive to invest in more predictive underwriting technology for the simple fact that the GSEs guarantee risk on the loans and that the price of these guarantees is set by a simple and pre-determined FICO $\times$ LTV grid.

Nevertheless, there are some marginal reasons that originators may have incentives to detect borrower risk beyond the GSEs' pricing grid. First, there is a short window after origination but before loans are sold to GSEs where the originator still owns the loan and is consequently exposed to borrower credit risk. Second, there is the risk that loans are *put back* from the GSEs, which occurs if the borrower defaults very early in the life of the loan (in which case default is taken as *per se* evidence that the underwriting was fraudulent), or if as a result of default later on, the GSEs allege and prove fraud in the underwriting process.

Therefore, we provide evidence around how borrower performance varies with whether the originator was a fintech lender. We run the following loan-level regression:

$$CreditEvent_i = \beta Fintech_i + FE + \epsilon_i \tag{24}$$

$$\tag{25}$$

Here, $CreditEvent_i$ is an indicator for a given credit event. We test (1) whether the loan becomes 30-days delinquent within the first three years of origination, (2) whether the loan becomes 60-days delinquent within the first three years of origination, (3) whether the loan becomes 90-days delinquent within the first three years of origination, (4) whether the loan is put back to the originator within the first three years of origination, and (5) whether there is a foreclosure on the borrower within the first three years of origination. $Fintech_i$ is a zero-one indicator for whether the lender is a fintech lender. FE is a collection of lender type, binned borrower characteristics, and market fixed effects. The results are shown in Table A6.

As shown in Columns (1)–(3), we find no statistically significant relationship between fintech and 30-, 60-, and 90-day delinquency. In columns (4) and (5), we find a small negative relationship but the results are again not statistically significant. Putbacks shown in column (4) are of potential consequence to orignators and servicers because it imposes a cost on the originator and terminates the servicing contract. Here, we find that fintech technology makes no difference for this economically relevant outcome for both servicer and originator. Foreclosures are also potentially important to servicers as it terminates the servicing contract. Together, the results suggest that fintech lenders do not possess any underwriting advantage in originating loans.

A.4 Search Intensity Match Details

This section details the search intensity match used in table 6. We start by splitting each HMDA yearly file into "denied" and "executed" datasets where executed denotes loans that were originated. We limit the sample to applications and loans for refinancing only. In each dataset, we create a matchkey consisting of combinations of applicant characteristics. To identify borrowers, we use a set of characteristics that are immutable between *application attempts*. These characteristics include,

- loan type: Indicator for FHA or conventional loan
- derived dwelling category: single family or multifamily home type
- business or commercial purpose
- occupancy type: owner occupied or investor
- loan amount: Amount of the loan (Note that these are rounded in the data. It's possible that borrowers re-apply for a differenet loan amount but because the value is already an approximation, we use it as is. We assume that it is unlikely for loan amounts to change significantly between applications. For refinancings where the loan needs to replace an existing balance, this is even less likely to change.)
- census tract
- county code
- applicant ethnicity
- co applicant ethnicity (note that if there is no co-applicant, this received a specific encoding)
- applicant race 1
- co applicant race 1
- applicant sex
- co applicant sex
- income
- lien status: First lien or subordinate lien

For observations in the denied set, these characteristics define a chained set. For observations in the executed set, any observations which are not unique along these characteristics are removed. These keys are then used to conduct a one-to-one match between denials and executed observations. By definition, this method creates a matched set of loans with at least one documented failure. However, there are a large number of unmatched applications remaining. For our analysis, we treat these loans as loans which were originated on the first try or loans which were never successfully executed. For the final dataset, we take a 5% random sample of the full data including unmatched orinated loans, unmatched denials, and matched chains.[11]

To facilitate analyses, we define several variables which classify the type of search experience. *Applications* denotes the total number of applications associated with a chain. This includes the originated loan and any matched denials. For unmatched denials, this includes the total number of applications and for unmatched originated loans, the applications number is one. This is our main dependent variable of interest. On the right side, we define a Fintech indicator for any application with a Fintech lender. This includes applications with Fintech lenders which were not executed. The second variable of interest is an indicator for Fintech Executed. By contrast to the Fintech indicator, this variable is only set to one for *originated* Fintech loans, all Fintech denials are set to zero.

For the analyses in the main paper, we use the full dataset including unmatched loans. However, one might be concerned that some loans are unmatched due to the algorithm implemented. In appendix table A8, we include a column that restricts the sample to the matched set. These are loans with at least one failed attempt before being executed. This is a smaller, more restrictive sample but it does not suffer from the potential concern with the unmatched loans.

[11]Note that the randomization is conducted at the chain level, not the individual HMDA observation level.

Table A1: Within lender-month integration shares

Note: The figure plots lender-month integration shares. The sample is a 1% random draw from the FNMA and FHLMC origination-level dataset. For each lender-month, the plot shows the proportion of all of their originated loans for which they are also the servicer.

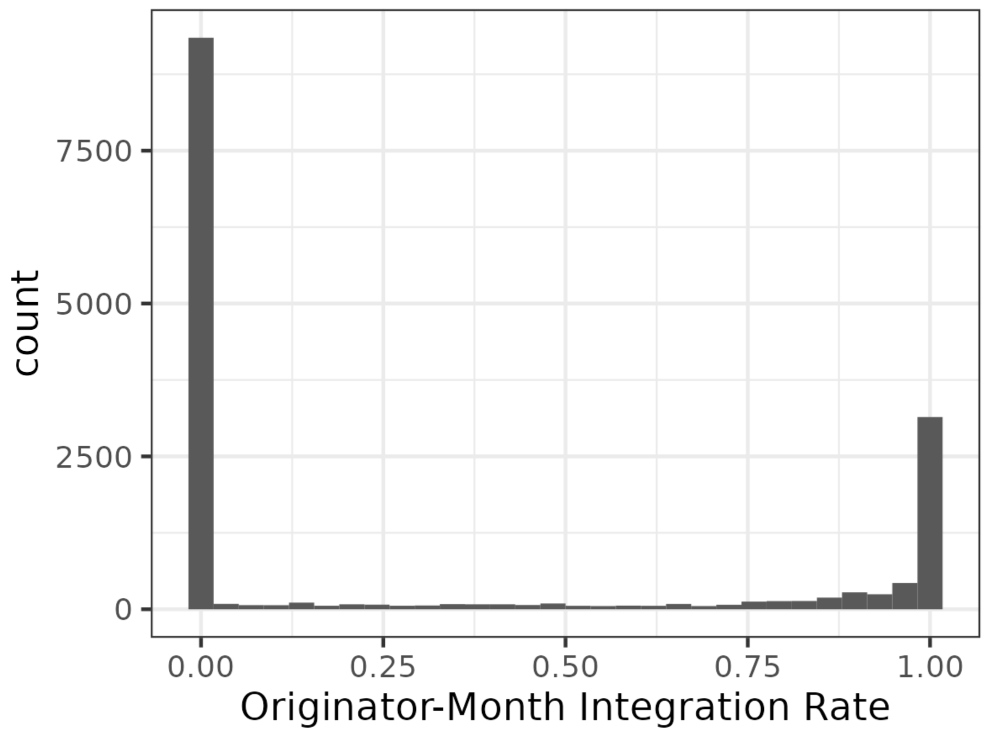
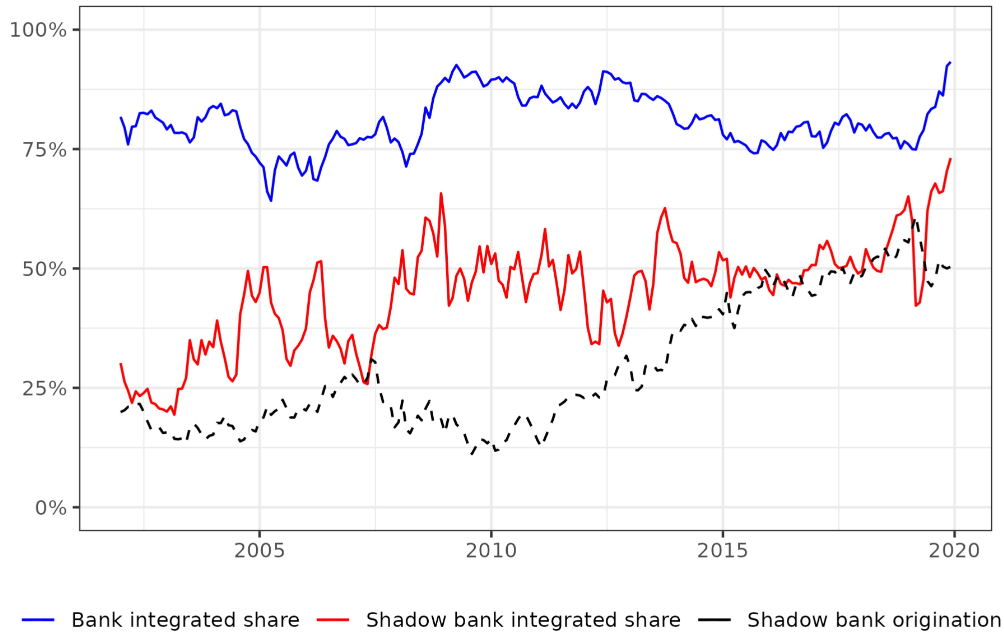


Table A2: Does shadow bank share drive integration share?

Note: This table shows descriptively what explains the aggregate integration share. Panel A shows the share of traditional bank originations that are integrated (blue), the share of shadow bank originations that are integrated (red), and the shadow bank market share (black, dashed line). Panel B shows a regression of aggregate integration share on shadow bank origination share (Column (1)), bank integration share and shadow bank integration share (Column (2)), and all three (Column (3)).

Panel A: Lender type integration share and shadow bank origination share



Panel B: Explanatory power regression

	Dependent variable:		
	Aggregate integration share		
	(1)	(2)	(3)
Shadow bank origination share	-0.265^{***}		-0.288^{***}
	(0.028)		(0.007)
Bank integration share		0.986^{***}	0.774^{***}
		(0.042)	(0.015)
Shadow bank integration share		0.053^{**}	0.243^{***}
		(0.022)	(0.009)
Observations	216	216	216
R^2	0.292	0.736	0.971
Adjusted R^2	0.288	0.734	0.970
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A3: Recaptured rate decomposition

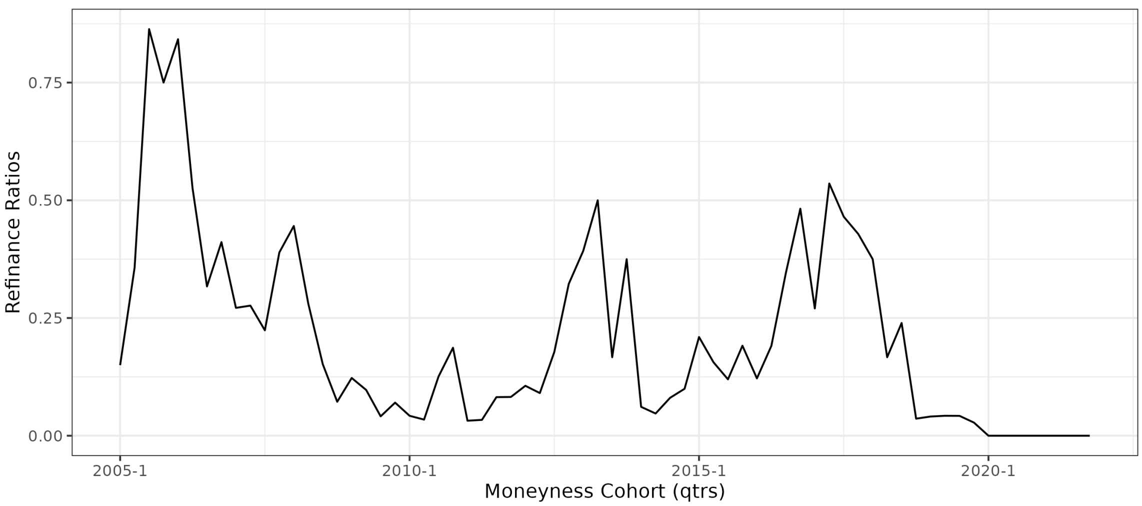
Note: This table examines existing and new interest rates for recaptured loan refinances. The sample is the forward-linked set of refinancings. We distinguish lenders based on “Fintech recapture” (fintech loans which are recaptured), “Fintech new borrower” (fintech refinancings where the previous lender was different), and “Non-fintech recapture” (recaptured loans where the lender was not a fintech lender). In Column (1), the left-hand side variable is the rate of the loan that is refinanced. In Column (2), the left-hand side variable is the new rate at which the loan is refinanced. $E[Y]$ is the mean of the left-hand side variable. All columns include lender type (bank versus shadow bank) fixed effects, new loan characteristic fixed effects, borrower controls, and market (3-digit zip code $\times$ year) fixed effects. The new loan fixed effects are interactions of HMDA variables: debt-to-income ratio bins, combined loan-to-value bins, bins of borrower income, and applicant age. Continuous origination controls are debt-to-income, CLTV, original loan size, and original loan term. Standard errors, clustered at the lender-county level, are shown in parentheses.

	Dependent variable:	
	Old rate	New rate
	(1)	(2)
Fintech recapture	-0.168^{***}	-0.012
	(0.018)	(0.012)
Fintech new borrower	0.020^{***}	-0.042^{***}
	(0.006)	(0.004)
Non-fintech recapture	0.058^{***}	0.049^{***}
	(0.012)	(0.015)
E[Y]	4.16	3.01
Lender Type FE	Y	Y
Borrower New Loan FE	Y	Y
Borrower Controls	Y	Y
Market FE	Y	Y
Observations	78,373	78,373
Adjusted R^2	0.429	0.599
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A4: Refinance rates

Note: Panel A depicts cohort-level refinancing rates over time. This is a 1% sample taken from the monthly loan-level performance dataset provided by FNMA and FMHLC. Each month, we take the difference between a loan's current interest rate and the prevailing mortgage rate (we use the average of all mortgages originated in the economy that month). Loans who are within three years of their potential rate improvement exceeding 50 basis points ($r_{old} - r_{prevailing} > 0.5$) is included in the sample. Each cohort depicted on the x-axis consists of loans which first became in-the-money that quarter. Then, the y-axis plots the share which has refinanced within 3 years of that date. Panel B shows a different version of these refinancing rates. Rather than cohorts, the x-axis shows all loans still active in that month for which the in-the-money criterion holds. These are loans that would benefit from refinancing. The y-axis shows the proportion of loans which do refinance that month. Loans that do not refinance reappear the following month if they are still in-the-money.

Panel A: Refinance propensity (by cohorts)



Panel B: Refinance Propensity (monthly)

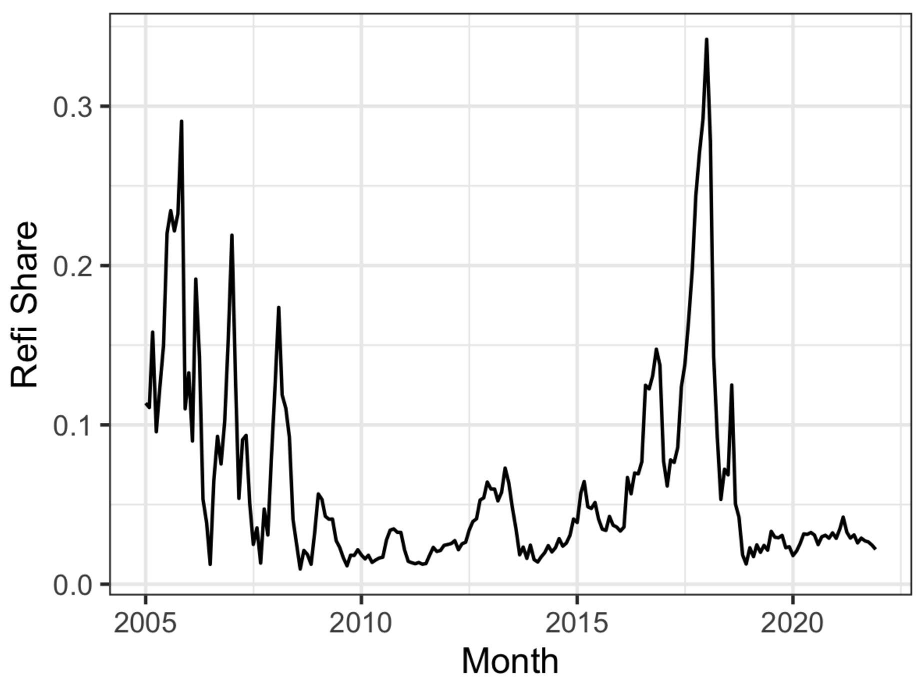


Table A5: Proportional Hazard Results

Note: Panel A below shows results from a cox proportional hazard analysis of fintech lenders. Age is defined as months since the loan was originated. A "death" is defined as exit through refinancing while "Fintech" is a zero-one indicator for whether or not the loan is originated by a fintech lender. Panel B shows kaplan-meier plots comparing survival probabilities for fintech lenders with non-fintech ledners. We include the results in panel A to show the survival probability of an exit event with the inclusion of borrower controls. The coefficient on Fintech is 0.064. Taking the exponential, $exp(0.064) = 1.06$ indicating that borrowers with fintech lenders are 6% more likely to refinance. The controls include lender type (bank versus shadow bank) fixed effects, market fixed effects and continuous borrower controls, debt-to-income, CLTV, original loan size, and original loan term. The sample is limited to loans for whom $r_{old} - r_{prevailing} > 0.5$ and loans that are younger than 45 months.

Panel A: Proportional Hazard Results

	Dependent variable:
	age
Fintech	0.664***
	(0.025)
Observations	596,821
R^2	0.014
Max. Possible R^2	0.553
Log Likelihood	−236,049.300
Wald Test	11,143.830*** (df = 7)
LR Test	8,521.517*** (df = 7)
Score (Logrank) Test	10,830.420*** (df = 7)
Note:	*p<0.1; **p<0.05; ***p<0.01

Panel B: Refinance hazard rates

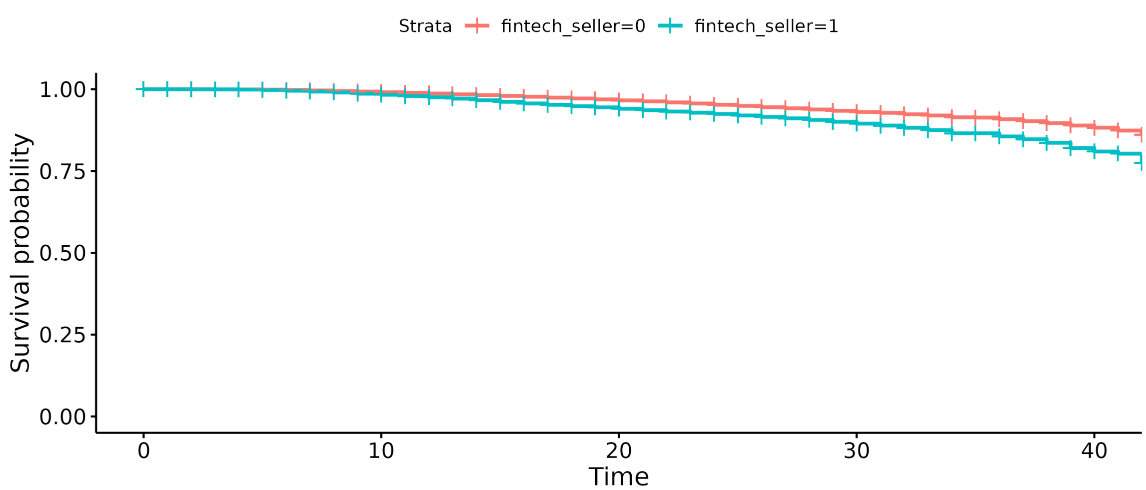


Table A6: Delinquency and default Rates

Note: This table shows delinquency rates for integrated and fintech lenders. We examine a 1% random draw of GSE loans originated between 2013 and 2021. The sample is limited to 2013 and onwards because this is when Fintech sellers begin to gain market share. The left-hand side variables are (1) whether the loan becomes 30-days delinquent within the first three years of origination, (2) whether the loan becomes 60-days delinquent within the first three years of origination, (3) whether the loan becomes 90-days delinquent within the first three years of origination, (4) whether the loan is put back to the originator within the first three years of origination, and (5) whether there is a foreclosure on the borrower within the first three years of origination. $Fintech_i$ is a zero-one indicator for whether the lender is a fintech lender. Each regression includes lender type (bank vs. non-bank) fixed effects, continuous borrower controls, and market FE is a collection of lender type, binned borrower characteristics, and market fixed effects. Standard errors, clustered at the zip-code level are shown in parentheses.

	Dependent variable:				
	30 DPD	60 DPD	90 DPD	putback	foreclose
	(1)	(2)	(3)	(4)	(5)
Fintech	0.0002	0.004	0.003	−0.00003	−0.00001
	(0.004)	(0.003)	(0.003)	(0.0001)	(0.00002)
E[Y]	0.013	0.007	0.005	0.000	0.000
Lender Type FE	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y
Market FE	Y	Y	Y	Y	Y
Observations	11,029,224	11,029,224	11,029,224	4,579,875	4,579,875
R^2	0.038	0.035	0.030	0.028	0.050
Adjusted R^2	0.029	0.026	0.021	0.006	0.028
Note:					*p<0.1; **p<0.05; ***p<0.01

Table A7: Fintech Recapture over Targets

Note: The table shows results from regressions of recaptured status on a fintech lender indicator. The sample consists of all loans in the forward-linked refinancing dataset. The dependent variable is one if the refinanced loan was recaptured and zero otherwise. The columns show results for different subsets of borrowers based on their potential rate improvement at the time of the refinancing. The table indicates whether or not the results include lender type (bank versus shadow bank) fixed effects, market fixed effects, fixed effects associated with loan charactersitics of the new refinancing loan, and continous borrower controls for the loan *at origination of the original loan.* Note that the coefficients of interest are robust to which set (origination or refinancing) borrower controls are used. The new loan fixed effects are interactions of HMDA variables: debt-to-income ratio bins, combined loan-to-value bins, bins of borrower income, and applicant age. Continuous origination controls are debt-to-income, CLTV, original loan size, and original loan term. Finally, market fixed effects are 3-digit zip code × year. Standard errors, clustered at the lender-county level, are shown in parentheses.

	Dependent variable:			
	Recaptured refinance			
	(1) $0.5 - 0.75$	(2) $0.75 - 1$	(3) $1 - 2$	(4) > 2
Fintech	0.138***	0.156***	0.089***	0.017
	(0.024)	(0.026)	(0.009)	(0.031)
E[Y]	0.16	0.15	0.13	0.10
Lender Type FE	Y	Y	Y	Y
Borrower New Loan FE	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
Market FE	Y	Y	Y	Y
Observations	11,443	11,830	30,230	6,229
Adjusted R^2	−0.035	0.057	0.133	0.030
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A8: Fintech borrower shopping

Note: This table examines the shopping behavior of fintech borrowers. Panel A examines borrower search behavior by regressing the number of mortgage applications in a given application spell on whether the spell includes a fintech search or origination. *Applications* counts the number of searches. *Fintech application* and *Fintech lender* are indicators for whether there is a fintech application or a fintech origination in the spell, respectively. Columns (1)-(2) include all loan spells, Columns (3) restrict the sample to those with an origination. Colums in both panels include, as indicated, lender type fixed effects, borrower controls, continuous borrower controls, and market fixed effects. Lender type is an indicator variable for bank vs. non-bank lenders. Borrower controls are interacted fixed effects of debt-to-income ratios, combined loan-to-value ratios, applicant income, and age. Continuous origination controls are debt-to-income, CLTV, original loan size, and original loan term. Market fixed effects are three-digit zip × year of the HMDA record.

Panel A: Fintech borrower search behavior

	Dependent variable:	
	Applications	
	(1)	(2)
Fintech application	-0.004^{***}	
	(0.001)	
Fintech lender		-0.004^{***}
		(0.001)
E[Y]	1.05	1.05
Lender Type FE	X	X
Borrower Controls	X	X
Market FE	X	X
Observations	1,010,492	1,010,492
Adjusted R^2	0.008	0.008
Note:	*p<0.1; **p<0.05; ***p<0.01	

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