FinTech Mortgage Lenders Solving or Exploiting a Friction? Evidence on Risk Layering and Prepayment Risk of Conforming Loans

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ABSTRACT

Fintech mortgage lenders have become an increasingly important source of mortgage credit in the US. Using loan-level data on mortgages sold to Fannie Mae and Freddie Mac (GSEs), I find that compared to traditional lenders, Fintech lenders are more likely to address credit demand from low credit score borrowers. However, they may be able to exploit two frictions in the GSEs' pricing and securitization setup. First, Fintech loans tend to have more risk layers conditional on paying the same guarantee fee, which are charged 15 basis points less of interest rate but translate to 0.5% higher delinquency rate ex-post. Second, Fintech loans get prepaid more often (11%). They get cross-subsidies in the to-be-announced mortgage-backed-securities market since these loans are pooled together with low prepayment risk loans in the same contract.

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Chapter 1

Introduction

Evaluation of creditworthiness plays a central role in lenders' day-to-day business. Consumers' access to credit and cost of credit are greatly affected by such evaluations. In recent years, some lenders and financial technology (Fintech) companies are looking to use alternative forms of data and new machine learning techniques that utilize big data to assist their loan approval and pricing decisions. Among loan markets, US residential mortgage markets, given its size, is arguably the one in which technology has had the largest economic impact thus far.

It is important to understand how Fintech lenders make loan approval and pricing decisions. If Fintech lenders can assess credit using alternative forms of data and big-data algorithms in a way different from and more precise than traditional lenders do,[1] they may be able to expand credit supply, lower credit price and increase consumer surplus, especially for people who face high barriers to accessing credit or have to pay much for credit. However, if Fintech lenders develop algorithms to game the current market structure and to serve their own interests by selecting and price discriminating against borrowers with desired characteristics,[2] it might embed an intensified moral hazard and adverse selection problem, might come at the cost of consumer surplus,

[1] Fuster, Plosser, Schnabl and Vickery (2018a) shows that technological innovation has improved the efficiency of mortgage lending by processing mortgage applications about 20% faster than other lenders without bringing in higher default rate.

[2] Bartlett, Morse, Stanton and Wallace (2017) and Fuster, Goldsmith-Pinkham, Ramadorai and Walther (2018b) both find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning techniques.

and may even increase the overall risk of the credit market.

Testing the effectiveness of credit decisions through the use of new technology directly is empirically challenging, as alternative data collected by lenders are unobservable to econometricians and lenders' algorithms are black-box. However, the conventional conforming securitized mortgage loan market by the Government Sponsored Enterprises (GSEs), namely Fannie Mae and Freddie Mac, serves as a playgroup for us to bring light into the black box. GSEs set underwriting standards that decides the eligibility of loans for them to purchase, and these underwriting standards are mostly based on specific observables, e.g., credit score (FICO), loan-to-value ratio (LTV), debt-to-income ratio (DTI) and etc.. A comparison on originated loans distribution and risk features as spoken by realized loan outcomes along these observables between traditional lenders and Fintech lenders enables us to draw implications on Fintech lenders' use of additional data on top of observables required by GSEs for borrower selection.

Fannie Mae and Freddie Mac have standardized loan pricing and securitization process, which provides opportunities for lenders to game the current market structure. With respect to loan pricing, the GSEs charge lenders a guarantee fee (g-fee) that prices credit risk across FICO and LTV cells, which further is passed on to the borrowers through interest rates.[3] However, additional risk layering is not priced in the g-fees. As long as a risk layering fits the GSEs' underwriting guidelines, it does not bring additional cost to mortgage lender.[4] Risk layering choice conditional on g-fees reflects lender risk appetite. Moreover, markups on top of the guarantee fees (and market interest rate) reflect lenders' discretion, possibly arising from market power or strategic volume positioning.

Similar to the lack of risk layering pricing by the g-fee, there is a lack of prepayment

[3] Bartlett et al. (2017) uses the same identification to study racial/ethnic discrimination. The loan-level price adjustment (LLPA) matrix specifies how GSEs price credit risk, which is accessible at https://www.fanniemae.com/content/pricing/llpa-matrix.pdf.. Fannie Mae and Freddie Mac guarantee fees reports provide a comprehensive description of how guarantee fee works. See https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/GFee-Report_12-10-18.pdf for the most recent version.

[4] There is still some put-back risk. However, put-back risk becomes immaterial post 2008 (Goodman, Parrott and Zhu, 2015).

risk pricing by the to-be-announced (TBA) mortgage-backed-security (MBS) market. In a TBA trade, the GSEs agree to a sale price, but does not specify the actual pool number or which particular MBS securities will be delivered to the investor on the settlement day. If prepayment risk has a lender-specific component, it cannot be priced precisely in a TBA trade, as the to-be-delivered MBS security, thus its lender identity, is hidden information when the trade happens. Therefore, in this paper, I use a large dataset of loans sold to GSEs between June 2011 and December 2018 to study the selection, pricing and ex-post loan outcomes of Fintech mortgage lenders within the current GSEs' pricing and securitization framework.

To explore whether Fintech lenders serve a different group of borrowers from traditional lenders in terms of observable dimensions, especially the traditionally viewed high credit risk group, I compare the distribution of loan originations over the GSEs' g-fee grid. G-fee reflects GSEs' pricing of credit risk. I find that Fintech lenders are more likely to originate loans with low credit scores, and meanwhile, low LTV to compensate. This may reflect some sort of market segmentation where high FICO borrowers are matched with traditional lenders, while low FICO borrowers are matched with Fintech lenders.

To examine the overall credit risk, I compare realized risk features between loans originated by traditional lenders and Fintech lenders that have the same level of predicted risk. Predicted risk levels are predicted probabilities from a probit model that rely only on observable loan and borrower characteristics. Results show that the ex-post average probability of a loan being delinquent for 90+ days or default does not differ statistically significant regardless of being a Fintech loan or a traditional loan.

Given the lack of risk layering pricing by the g-fee, I find that conditional on g-fee, loans with one more layer of risk are 1.4% more likely to come from a Fintech lender. On top of g-fee (and market-wide interest rate), lenders have discretion in setting a premium in interest rate. I explore the heterogeneity of interest rate premium across loans with different risk layers conditional on g-fee. Surprisingly, Fintech lenders charge 7 basis points less of interest rate for loans with two risk layers and 15 basis points less of interest rate for loans with three or four risk layers. Since credit risk is insured by the GSEs and put-back risk is immaterial, such competitive pricing practice potentially reflects Fintech lenders' strategic volume positioning.

Turing to the implications on the lack of prepayment risk pricing in the TBA market, I find that Fintech loans are 11% more likely to get prepaid. However, I do not explore the underlying mechanisms in this paper. It could be that Fintech lenders put a lot of marketing effort in refinance products, which leads to quicker prepayment.[5] Regardless of the underlying reasons, lender-specific prepayment risk leads to cross-subsidization in the TBA market where prepayment risk is not individually priced.

Overall, my results suggest that Fintech lenders adopt technology that enables them to evaluate credit risks which potential facilitate financial inclusion. But at the same time, Fintech lenders might expand their market share through exploiting the current GSEs' underwriting and securitization features.

My findings do not necessarily imply how Fintech mortgage lending will evolve in the future. In my sample period, large banks including Wells Fargo had not adopted financial technology in mortgage origination, but now they do.[6,7] As technology advances and competition intensifies, the quantity and distribution of credit are likely to be influenced in a different way. Moreover, my results may not represent how advanced techniques are applied in loan markets other than mortgage market. The structure of conventional securitized mortgage market is a unique feature that other loan markets do not possess. However, my results do call for attention to what advanced technology could be used for in credit decisions including for serving lenders' own interests which may comes at the cost of distorting credit allocation.

This paper contributes to several strands of the literature in finance. This paper

[5] On the darker side, it could also be that contract terms in first loans are biased towards more prepayment. Fintech lenders trade off profits in the purchase mortgage and refinance mortgage. See anecdotal evidence by McLannahan (2015) on Quicken loans give low appraisals at loan origination. Also see (Agarwal, Ben-David and Yao, 2015) and Kruger and Maturana (2018) for empirical evidences on biased appraisals.

[6] For example, Wells Fargo and Bank of American rolled out digital mortgage applications in 2018. See at https://www.housingwire.com/articles/47134-wells-fargo-bank-of-america-reveal-true-impact-of-digital-mortgages.

[7] As Quicken Loans being the largest Fintech lender in the market during my sample period, the results are not driven by Quicken Loans only. Results hold if I exclude all loans originated by Quicken from the sample.

contributes to a growing literature on the role of technology in the US mortgage market. The most related paper is Buchak, Matvos, Piskorski and Seru (2018). They compare Fintech lenders to nonbank lenders and show that Fintech lenders serve more creditworthy borrowers and are more active in the refinancing market. In this paper, I compare Fintech lenders with all other traditional lenders and show that Fintech lenders serve borrowers with lower FICO and LTV, and tend to add more risk layers. Consistent with another key result in Buchak et al. (2018), Fintech lenders appear to charge a premium for provision of convenience. However, the premium is negative for loans with more risk layering features. Fuster et al. (2018a) provide evidence on how technology reduces frictions in mortgage lending, including lengthy loan processing, capacity constraints and inefficient refinancing, but find only limited evidence in the role of technology in expanding credit access to some constrained borrowers. In terms of distributional consequences of using machine learning algorithms, Fuster et al. (2018b) compare a linear probability model with the random forest model in predicting default on US mortgage market and find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning. Similarly, Bartlett et al. (2017) provide evidence that algorithm lending which utilizes big data would introduce illegitimate statistical discrimination. Both traditional and Fintech lenders charge non-white borrowers 0.08% higher interest for purchase mortgages.

There is a strand of literature that discusses the role of GSE securitization in the mortgage market. Related to my findings, Pagano and Volpin (2012) study the trade-off of limiting transparency at the security issue stage: increased liquidity at the primary market vs. decrease liquidity at the secondary market. Vickery and Wright (2013) provide an overview of the TVA trading and liquidity issues in the agency MBS market, and provides suggestive evidence that the liquidity associated with TBA eligibility increases MBS prices and lowers mortgage interest rates. Complementary to their work, I take the agency MBS market structure as given, and show evidence that Fintech lenders are able to exploit the limited transparency at the security issue stage where lender-specific prepayment risk is not priced.

This paper also adds to the literature on the misaligned incentives of intermediaries. Most of the literature focus on pre-crisis period and explores potential causes of the mortgage crisis, e.g. Keys, Mukherjee, Seru and Vig (2010), Keys, Seru and Vig (2012), Agarwal et al. (2015), and Agarwal, Amromin, Ben-David and Evanoff (2016). This paper uses post-crisis data and provides implications on the role that technology might play in serving lenders' misaligned incentives and distorting credit allocation.

Finally, this paper contributes to the literature on price dispersion in consumer credit markets. The literature has been focusing on search cost (Alexandrov and Koulayev, 2018; Argyle, Nadauld and Palmer, 2017), negotiation (Allen, Clark and Houde, 2014a,b), and lender selection (Agarwal, Grigsby, Hortaçsu, Matvos, Seru and Yao, 2017). In the context of this paper, price dispersion may comes from vertical product differentiation (Hortaçsu and Syverson, 2004; Wildenbeest, 2011) as well as lender selection.

The rest of the paper is organized as follows. In Chapter 2, I discuss the data and sample selection criteria. Detailed institutional knowledge on GSEs' underwriting practice and securitization process is described in Chapter 3. In Chapter 4, I present my methodology and empirical results for testing Fintech lenders' selection on credit risk profiles and ex-post loan outcomes. I show evidence of potential exploitation of risk layering and prepayment risk in Chapter 5. Lastly, Chapter 6 concludes.

Chapter 2

Data and Statistics

2.1 Fannie Mae and Freddie Mac Data Sets

The main data used in this paper is from the Fannie Mae and Freddie Mac single-family loan performance data sets. The Fannie Mae and Freddie Mac data sets provide origination and performance data on a subset of these GSEs' 30-year, fully amortizing, full documentation, single-family, conforming fixed-rate mortgages that are the predominant conforming contract type in the US. Borrower and loan characteristics at origination are provided, including LTV, DTI, FICO, etc. For each loan acquired by the GSEs, monthly payment history including delinquency and prepayment status are tracked and reported in the monthly performance panel data. In the event of a prepayment, the reasons for prepayment, namely refinancing or house sale, are not identified though. Moreover, importantly, in both Fannie Mae and Freddie Mac data, for lenders that represent more than one percent of volume in loans sold to the GSEs as represented by the original unpaid principal balance, the name of the mortgage lender is disclosed. This piece of information helps in identifying lenders over time and classify lenders into traditional ones and Fintech ones. To classify lenders into traditional lenders and Fintech lenders, I follow the methodology proposed by Buchak et al. (2018). Buchak et al. (2018) classify a lender as a Fintech lender if the lender has a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender. [1] Thus, my sample focuses on large lenders.

The loans in my sample were originated between June 2011 and December 2018. June 2011 is the first month when Fintech lenders represent more than 0.5% of the originated loans in the above sample. The monthly performance data runs through June 2019. To reflect current underwriting guidelines of the GSEs, I exclude loans with LTV greater than 105, DTI greater than 50, or FICO less than 620. Furthermore, loans in my sample has no missing information in LTV, DTI, FICO, loan amount, interest rate, and geographic identifiers, namely, state and 3-digit zip code. This leaves me with 8,691,496 mortgages in the main testing sample.

Figure B-2 plots Fintech mortgage lenders origination shares by month based on the sample and lender classification described above. The market share increased from less than 1% in 2011 to around 17% in 2018. Table A.1 provide summary statistics of mortgage originations, in total and by lender type, based on the sample described above. First, Fintech lenders originate loans to borrowers with relatively low FICO and low LTV, but more layers of risk relative to traditional lenders. Second, on loan pricing, Fintech lenders charge higher interest rate on average. Moreover, Fintech lenders tend to originate smaller loans with shorter maturity.

2.2 Form ABS-15G

To identify lenders of mortgage loans that are pooled together in an MBS product, I rely on data from GSEs' SEC filings. On January 20, 2011, the SEC adopted final rules to implement Section 943 of the Dodd-Frank Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act) related to asset-backed securities (ABS). Section 943 of the Dodd-Frank Act requires the SEC to prescribe regulations on the use of representation and warranties in the market for ABS. Specifically, it requires any

[1] Bartlett et al. (2017) uses the same classification. Fuster et al. (2018a) classify a lender as a Fintech lender if it is possible to obtain a preapproval online. According to Fuster et al. (2018a), these two classifications are similar with only minor differences with respect to the classification of few smaller lenders.

securitizer to disclose fulfilled and unfulfilled repurchase requests across all trusts aggregated by the securitizer so that investors may identify asset originators with clear underwriting deficiencies. In compliance with the new regulation, Fannie Mae and Freddie Mac file Form ABS-15G each quarter to set forth any repurchase activity during the applicable quarter. Particularly, Form ABS-15G presents information on the name of the originator of the underlying assets, the number and dollar amount of each underlying asset, and would include all originators that originated assets in the asset pools for each issuing entity.

2.3 TRACE

I further obtain data on TBA prices from TRACE. TRACE stands for Trade Reporting and Compliance Engine. It is operated by FINRA, the Financial Industry Regulatory Authority. TRACE covers product-level information and transactions for securitized products including mortgage-backed securities, including agency pass-through MBS that are traded to be announced (TBA). Specifically, I obtain from TRACE a master file of MBS securities that are eligible for a TBA contract, and a daily price file for TBA contracts.

One limitation of the dataset is that it does not provide the entire transaction history of an MBS security. In contrast to a CUSIP, which is constant over the life of the security, an MBS is identified by different RDIDs over the life of the security. This is due to the amortization of the securities.[2] However, the TRACE system only stores the most current version of the RDID and one prior version. Therefore, archived RDIDs are not available in the real-time disseminated data.

[2] A RDID contains information about the original coupon, weighted average coupon, original maturity, weighted average maturity, original LTV, average loan size, and weighted average loan size. See https://sec.gov/rules/sro/finra/2013/34-69702.pdf.

Chapter 3

Institutional Details

3.1 The GSE Lending Process

When a mortgage lender originates a loan and sells it to the GSEs, GSEs determines its eligibility based on an automated underwriter system (Desktop Underwriter for Fannie Mae, and Loan Prospector for Freddie Mac). Inputs to the automated underwriter system include credit score (FICO), loan-to-value ratio (LTV), debt-to-income ratio (DTI), property value, etc. If the GSEs accept the loan, the lender sells the mortgage to the GSE, and receives a cash transfer to compensate. GSEs then securitize the mortgages and insure against credit risk.[1]

GSEs do not provide insurance for free. Instead, when GSEs buy a mortgage from a lender, the GSEs charge a guarantee fee (g-fee) to cover expected default loss and operational costs. The g-fee only varies in a FICO and LTV grid. Therefore, my first analysis would start with comparing loan distributions over the GSE grid between traditional lenders and Fintech lenders. Since such selection is priced by g-fee, it reflects lenders' preference to serve different market segments.

When purchasing a loan, GSEs require lenders to evaluate the overall level of serious delinquency risk by taking into consideration any layering of risk factors. The Eligibility Matrix at the GSEs identifies the following risk elements: credit score, LTV,

[1] In recent years, GSEs are not the only entity that bears credit risk. They design a few credit risk transfer products to transfer part of the credit risk to the market.

occupancy, loan purpose, DTI, and financial reserves. On top of a chosen FICO and LTV cell, layering of risk factors is constrained but not priced by the GSEs. For example, the purchase of a single unit principal residence must have LTV ratios no higher than 95%, a credit score of at least 680, and a DTI ratio no greater than 36%. If the DTI ratio is greater than 36%, a higher credit score is required. But if the LTV ratios are less than 75%, a credit score as low as 620 is permitted.[2] Conditional on a FICO and LTV cell, any additional layers of risk reflects the lenders' risk appetite.

In later sections, I study lenders' preference to serve different market segments, as measured by distributions over FICO and LTV grid; and lenders' risk appetite, as proxied by additional risk layers conditional on a given FICO and LTV cell.

3.2 The GSE Securitization Process

Creating a single-family MBS begins with a group of loans. The loans are underwritten by lenders to borrowers to finance properties. The GSEs acquire mortgage loans from lenders and then securitize those loans. The most common type of securitization is through lender swap transactions. As illustrated in Figure B-1, in a lender swap transaction, a mortgage lender delivers a pool of mortgage loans to the GSEs in exchange for a GSE-issued MBS backed by these loans.[3]

A major type of GSE-issued MBS is fixed-rate mortgage MBS, which, as its name suggests, are backed by fixed rate mortgages. In the secondary mortgage market, fixed-rate MBS can trade on either a TBA (To-Be-Announced) or a specified pool basis. However, more than 90 percent of agency MBS trading volume occurs in the TBA market (Vickery and Wright, 2013). TBA market is a liquid forward market for trading agency MBS. In a TBA trade, the seller of MBS agrees to a sale price, but does not specify the actual pool number or which particular MBS securities (identified by CUSIPs) will be delivered to the buyer on settlement day. Only limited information

[2]The example is taken from Fannie Mae Selling Guide at https://singlefamily.fanniemae.com/media/22431/display

[3]For details, refer to the single-family MBS basics at https://fanniemae.com/resources/file/mbs/pdf/basics-sf-mbs.pdf.

is known at a forward contract trade. This includes maturity, coupon rate, MBS issuer (Fannie Mae or Freddie Mac), approximate face value, and settlement date. Two days before the settlement date, the seller of the TBA must provide CUSIP information to the purchaser of the TBA contract. Such convention allows trading to be concentrated in only a small number of liquid forward contracts. It is believed that the liquidity associated with TBA eligibility increases MBS prices and lowers mortgage interest rate (Pagano and Volpin, 2012).

MBS investors bear two forms of risks: prepayment risk and interest rate risk, as credit risk is insured by the GSEs. Prepayment risk is the risk that borrowers may prepay their mortgages more quickly or slowly than expected, thereby affecting the investment's average life.[4] Interest rate risk is the risk that the price of the security may fluctuate over time.

In the TBA forward contract, MBS securities are not specified at trade. It also means that the lenders who originate loans that back the particular securities are not known. If prepayment risk has any lender-specific component, this is not going to be priced precisely in a TBA trade. This is because MBS securities backed by loans originated by different lenders are pooled together in a single TBA contract. Lenders who originate loans with high prepayment risk gain from such cross-subsidization, while lenders whose loans have low prepayment risk lose. In a later section, I am going to explore the differences in prepayment risks between traditional lenders and Fintech lenders, and provide evidence for such cross-subsidization.

[4]Loans in the sample do not have prepayment penalty.

Chapter 4

Selection of Market Segment and Credit Risk

In this section, I compare Fintech lenders with traditional lenders along two dimensions: preference to serve different market segments, as measured by distributions over the pre-specified FICO and LTV grid by the GSEs guarantee fee; and the average ex-post deliquency and default risk.

4.1 Selection Results

The first analysis is to study whether Fintech lenders serve a different group of borrowers from traditional lenders in terms of observable dimensions, especially the traditionally viewed high credit risk group. GSEs charge guarantee fees for purchased loans to insure against credit risk. As introduced in Chapter 3, g-fee only varies across FICO and LTV cells. To start with, I plot the distribution of loan originations over the FICO and LTV cells for traditional and Fintech loans separately in Figure B-3. Fintech lenders tend to originate loans with lower FICO and lower LTV than traditional lenders.

To study borrower selection in a more systematic way, I estimate the following linear probability model:

$$Pr(Fintech_{ist} = 1) = \beta_0 + \beta_1 FICO_{ist} + \beta_2 LTV_{ist} + \beta_3 FICO_{ist} \times LTV_{ist} + \delta_s + \gamma_z + \epsilon_{ist} \tag{4.1}$$

where an observation is a mortgage i in state s in year-month t. Fintech is an indicator which equals 1 if the loan is originated by a Fintech lender. FICO and LTV are contracting terms at loan origination. Dummies for state times year-by-month are also included. Results are reported in Table A.2. Consistent with the pattern in Figure B-3, conditional on a 80 LTV, a decrease in FICO by 20 points leads to 0.7% more likely for a loan to be originated by a Fintech lender. Similarly, conditional on a 740 FICO, a decrease in LTV by 5 points translates into a 0.7% higher probability for a loan to be originated by a Fintech lender. The piece of evidence suggests that Fintech lenders may be able to expand credit supply to low credit score borrowers, but at the same time, compensate by requiring a low LTV, or in other words, high collateral. This suggests that Fintech lenders seem not to be taking risks on every dimension.

4.2 Credit Risk

Are ex-ante risky borrowers indeed risky ex-post? In other words, if Fintech lenders are able to assess additional forms of data on top of the hard information required by the GSEs more efficiently and therefore, can select creditworthy borrowers on the margin (Chernenko, Erel and Prilmeier, 2018), we would expect to see superior (or at least equal) ex-post performance conditional on ex-ante characteristics. To test this hypothesis, I study the ex-post performance of Fintech loans compared to traditional loans with similar predicted performance based on observables only.

To predict loan outcome using observables, I first estimate the following probit model to forecast delinquency using loan and borrower characteristics:

$$Pr(Outcome_{ist} = 1) = \Phi(\beta_0 + \beta_1 InterestRate_{ist} + \Gamma X_{ist} + \delta_s + \gamma_z + \epsilon_{ist}) \tag{4.2}$$

where an observation is a mortgage i in state s in quarter t. I consider two outcome variables that proxy for credit risk, 90+ days delinquent and default in 36 months after loan origination. Interest rate, LTV, FICO, Risk layers (specifically, cash-out refinance flag, investment purpose flag, high DTI flag, and one-borrower flag) and other contracting terms at loan origination are used as forecasting variables. Dummies for state and year-by-month and dummies for GSEs' FICO and LTV grid are also included (Fuster et al., 2018b). Columns (1) and (2) of Panel A in Table A.3 show the forecasting results. Not surprisingly, interest rate are positively correlated with delinquency and default.

In the next step, I calculate predicted delinquency and default probability using coefficient estimates from Panel A in Table A.3. Based on the predicted delinquency, default or prepayment probability, I separate loans into 12 groups. Group 1 represents the group with lowest predicted probability, and group 12 represents the group with highest predicted probability. Then, for each group, I compare the ex-post delinquency or default outcome between Fintech loans and traditional loans.

Figure B-4 plots the ex-post 90+ days delinquency rate within 36 months since origination for traditional and Fintech lenders by predicted delinquency groups. The number of loans in each group is also plotted on the right y-axis. The table below the graph reports the t-test on the difference in delinquency rate between the two groups. The figure suggests that for the high predicted delinquency rate group, with predicted delinquency rate greater than 1.5%, the ex-post delinquency rate for Fintech loans is lower by 0.2% – 0.5%. But for low predicted delinquency rate groups, the ex-post delinquency rate for traditional and Fintech lenders do not differ significantly. Overall, the effect is insignificant, as indicated by Column (1) in Panel B of Table A.3 where I regress ex-post delinquency on Fintech indicator and predicted delinquency rate.

Figure B-5 plots the ex-post default rate for traditional and Fintech lenders by predicted default groups. It suggests that for groups in the middle range of the predicted default rate (0.05% to 0.7%), the difference in ex-post default rate is statistically significant, and Fintech ex-post default rate is higher by 0.02% – 0.12%. Taken together, the overall difference is not significant though.

I end this section on a positive note. Fintech lenders seems to be able to address credit demand from low credit score borrowers, and at the same time, on average, Fintech lenders originate loans that are neither less risky nor more risky in terms of credit risk conditional on the observable characteristics.

Chapter 5

Exploitation on Risk Layering and Prepayment Risk

In this section, taken the GSEs' standard pricing and securitization process as given, I look into the possible exploitation by Fintech lenders.

5.1 Risk Layering

Previous evidence suggests that Fintech lenders may have been expanding their market share by entering the risky market segment as defined by the GSEs' g-fee grid. In the next, I answer the question that given the g-fee, how Fintech lenders behaves differently from traditional lenders.

5.1.1 Preference for Risk Layering

A key feature of the GSE underwriting process is that g-fee only varies across FICO and LTV cells, but fixed for a given FICO and LTV cell. In other words, additional risk layering conditional on the FICO and LTV cell is not priced differentially by the g-fee. Therefore, the next step in my analysis is to compare risk layering features between traditional and Fintech lenders conditional on FICO and LTV.

I define risk layers based on the Fannie Mae Selling Guide. For the sample of single-family, fixed rate mortgages, other than credit score and LTV, four additional layers of risk are identified: whether the loan is a cash-out refinance loan, whether the loan has an investment purpose instead of owner-occupied, whether the loan has a DTI that is greater than 45, and whether the loan has only one borrower which provides limited financial reserves.[1] Figure B-6 plots the distribution of the number of risk layers for traditional and Fintech lenders. The distribution for Fintech lenders shifts to the right, which means that Fintech lenders tend to originate loans with greater number of risk layers than traditional lenders.

To study risk layering features more rigorously, I estimate the following linear probability model:

$$Pr(Fintech_{ist} = 1) = \beta_0 + \beta_1 RiskLayers_{ist} + \gamma X_{ist} + \delta_{st} + \mu_{GSEgrid} + \epsilon_{ist} \tag{5.1}$$

where an observation is a mortgage i in state s in year-month t. Fintech is an indicator which equals 1 if the loan is originated by a Fintech lender. Control variables X_{ist} include FICO, LTV, an indicator for whether the loan is brokeraged or not, loan size and loan maturity. State-by-year-month fixed effects, and GSE g-fee grid on FICO and LTV are also included in the regression. Results are reported in Table A.4. If a loan had one additional risk layer, it is 1.4% more likely to be originated by a Fintech lender. Specifically, Fintech lenders tend to add risk layers by allowing a higher DTI, tighter financial reserves, and a cash-out refinance, but not through serving investment purpose.

5.1.2 Pricing of Risk Layering

After presenting evidence on Fintech lenders' risk appetite, the natural next step is to study how Fintech lenders differ from traditional lenders on pricing mortgages. Cost of borrowing is as important as access to and quantity of credit in terms of credit

[1] Financial reserves may come in the form of non-borrower income though, which is used frequently in Fannie Mae HomeReady loan. Non-borrower income is the income from people who live with the borrower but are not the actual borrowers, e.g. adult children. The income is used to give the lender reassurance that a borrower will be able to pay her mortgage despite DTI being greater than 45%.

allocation and consumer welfare.

Mortgage rates have three components. Market interest rate reflects the overall credit environment. Guarantee fee is charged to insure against credit risk. Moreover, On top of market interest rate and GSEs' guarantee fee, lenders have discretion in charging a premium in loan rate. Such premium may reflect lender fixed effects arising from cost of capital. It may also reflect market power or strategic volume positioning (Bartlett et al., 2017). Of particular interest is how premium differs with layers of risk.

To start with, I estimate the following regression:

$$\begin{aligned} Interest\ rate_{ist} = &\beta_0 + \beta_1 Fintech_i + \beta_2 RiskLayers_{ist} + \beta_3 Fintech_i \times RiskLayers_{ist} \\ &+ \Gamma X_{ist} + \delta_{st} + \epsilon_{ist} \end{aligned} \tag{5.2}$$

where an observation is a mortgage loan i in state s in quarter t, interest rate is the contract term at origination, Fintech and risk layers are defined the same as in 4.1. Other loan characteristics, state-by-year-by-month fixed effects and GSEs' FICO and LTV grids are included in the regressions. In alternative specifications, I use three-digit level zip codes as geographical identifiers. Table A.5 reports the results. I draw three interesting implications.[2]

First, consistent with Buchak et al. (2018), Fintech lenders appear to charge 12 basis points more than traditional lenders. This may reflect the fact the Fintech lenders on average have higher cost of capital. It may also reflect the convenience premium, as discussed in Buchak et al. (2018), since interest rate is disproportionally higher for high FICO borrowers who value and have willingness to pay for convenience.

Second, interest rate is an increasing function in the number of risk layers. Although credit risk is insured by the GSEs, lenders still bear the put-back risk. Put-backs can occur when the documentation on income, credit score, loan purpose, or appraisal value is falsified or missing. This increasing pattern may reflect the positive correlation

[2] This is result is not driven by the mortgage insurance type. For loans with high LTV or low FICO, private mortgage insurance is required by the GSEs. The mortgage insurance could be lender-paid, therefore, would be incorporated in the interest rate. My results still hold if I exclude the subset of mortgages that have lender-paid mortgage insurance.

between pub-back risk and number of risk layers.

Lastly, and most importantly, when looking at the interaction terms, Fintech lenders reduce the premium, and especially so as the number of risk layers increases. This goes against the market power assumption, under which Fintech lenders should charge higher premium (Gissler, Ramcharan and Yu, 2018). Instead, the evidence is consistent with strategic volume positioning. Fintech lenders may attract risky borrowers by reducing interest rate.

5.1.3 Ex-post Performance of Risk Layering

To evaluate the differences in ex-post performance between Fintech and traditional loans with different levels of risk layering, I modify the regression in Equation 4.2 by adding the Fintech indicator, and its interaction terms with various levels of risk layers. In Columns (1) and (2) in Table A.6, I report the effect of risk layering on loan ex-post credit risk. To start with, more risk layers translate into greater probability of delinquent or default for both traditional and Fintech loans. However, by looking at the interaction terms, Fintech loans with four layers of risk is 0.5% more likely to be delinquent, while Fintech loans with more than one layers of risk is 0.1% – 0.5% more likely to default. The effect is not ignorable given the overall delinquency and default rate (around 2%) has been dropping significantly after the 2008 financial crisis.

Putting it all together, evidence in this section shows that conditional on g-fee, Fintech lenders push towards originating loans with more risk layering. Surprisingly, interest rate is lower for such loans, potentially reflecting Fintech lenders' strategic volume positioning. Moreover, ex-ante risk layers do translate into greater probability of delinquency or default.

5.2 Prepayment Risk

5.2.1 Evaluation of Prepayment Risk

After GSEs purchase mortgages that satisfy their underwriting guidelines, GSEs would securitize the loans by issuing MBS securities. MBS investors are insured against credit risk by the GSE, but still, bear interest rate risk and prepayment risk. Since interest rate risk is a market wide risk, and comes from macro economic environment, I focus on the prepayment risk in this analysis. Prepayment risk is the risk that the value of the mortgage will change because of shocks to borrower prepayment behavior. When a mortgage is prepaid at par, the par value may differ substantially from the prior market value. Prepayment behavior is affected by a combination of factors, such as market rates, housing turnover, credit conditions, etc. The complex nature of prepayment risk makes it difficult to predict and thus to hedge against.

As discussed in Chaper 3, prepayment risk is only priced based on the expectation of all MBS securities that are eligible to be delivered through a TBA contract. But these MBS securities are backed by loans from different lenders. If certain lenders originate loans that have higher or lower prepayment risk, this is not going to be reflected in the TBA contract sale price. It is going to be priced in the particular MBS security on the secondary market after the TBA contract is settled.

First, I examine the average prepayment risk differentials conditional on observables. I follow the steps in Section 4.2 but change the outcome variable to ex-post prepayment within three years since origination. Figure B-7 plots the ex-post prepayment rate for traditional and Fintech lenders by predicted prepayment groups. On average, a loan is 11% more likely to get prepaid if the loan is originated by a Fintech lender.

To explore heterogeneity in Fintech loans propensity to prepay for various level of risk layers, I follow steps in 5.1.3 and report the results in Column (3) of Table A.6. By looking at the interaction terms of Fintech flag and various risk layers groups, we observe that a substantial part of prepayment behavior comes from Fintech loans with one or two risk layers.

Results above suggest that Fintech loans on average contain greater prepayment risk. When pooled together with traditional loans in a TBA contract, Fintech loans get cross-subsidies due to the lack of lender specific prepayment risk pricing.

5.2.2 Externalities

To assess the (lack of) prepayment risk pricing in a TBA contract, I assemble a dataset based on SEC ABS-15G filings and TRACE TBA and MBS files. From SEC ABS-15G, I extract information on MBS CUSIP, mortgage originator, total assets at origination. There are in total 1,075,960 unique CUSIPs for the entire time period of 1989 to 2020. Then, based on the names of mortgage originators, I classify Fintech originators following the definition of Buchak et al. (2018).

Not all MBS securities are eligible to trading on the TBA basis. To focus on TBA-eligible MBS securities, I obtain uniform-MBS CUSIP identifiers from TRACE MBS master file. This gives me 178,679 CUSIPs for issuance month in between Jun 2011 and Dec 2018. For each MBS, I calculate the share of assets that are from a Fintech mortgage lender. The top graph in Figure B-8 illustrates the distribution of Fintech share for 178,679 MBS securities. The majority of the MBS securities contains loans from only one lender, either a traditional lender or a Fintech lender.

TBA contracts are settled once in a month. The settlement date differs each month. For simplicity, I assume that MBS securities with the same issuance month are pooled together in one TBA contract (conditional on other contract features such as issuer, coupon and maturity). The bottom graph in Figure B-8 plots the trend of average Fintech asset share in a TBA contract. Consistent with the overall market share of Fintech lenders, we see an upward trend.

A TBA contract is identified by the issuer (Fannie Mae or Freddie Mac), maturity (10, 15, 20 or 30 years), coupon (with 25 basis points as the tick size), and settlement month. I calculate the monthly price of TBA trades at the year-month, maturity and coupon level, and call it the TBA price. To analyses TBA pricing of lender-specific prepayment risk, I run an OLS regression where I regress TBA price on Fintech share, market interest rate, and the interaction term. Results are reported in Table A.7. Each observation is at the year-month, coupon rate and maturity level. Column (1) excludes year-month fixed effects. TBA price is negatively correlated with market interest rate, since prepayment risk is higher when interest rate is high. Columns (2) and (3) includes the time trend fixed effects. In all specifications, TBA price does not load significantly on the Fintech share and its interation with the market interest rate. Given the fact that Fintech loans are 11% more likely to get prepaid, this evidence is consistent with a lack of pricing of lender-specific prepayment risk.

Due to the limitation of the MBS transaction data, it is hard to quantify the price of prepayment risk for individual MBS securities, and thus the magnitute of the potential cross-subsidization between traditional and Fintech lenders. Still, the qualitative analysis is able to suggest that Fintech lenders can benefit from more frequently prepaid loans.

Chapter 6

Conclusion

This paper provides new evidence on the use of technology in the US mortgage market by examining Fintech lenders' selection, pricing and ex-post performance given the current GSEs' underwriting and securitization practice.

Compared to traditional lenders, Fintech lenders seems to be able to address credit demand from low credit score borrowers better than traditional lenders, without resulting in higher credit risk conditional on observable characteristics required by GSEs' underwriting process.

Meanwhile, Fintech lenders potentially can take advantage of two key features of the GSEs' underwriting and securitization practice. First, there is a lack of pricing of risk layering activities conditional on FICO and LTV by the GSEs' guarantee fee. Fintech loans appear to have greater number of risk layers. Such loans are charged lower interest rate surprisingly, and are subject to greater delinquent and default rate.

Second, Fintech loans are more likely to be prepaid. But prepayment risk is not priced by individual MBS securities in the TBA market, as different MBS securities are pooled together, and the identity of the to-be-delivered MBS security is hidden information at a TBA trade. This imposes negative externalities to traditional lenders, since the overall prepayment expectation is higher, and thus results in a lower price of TBA contract.

My results suggest that Fintech lenders adopt technology that enables them to evaluate credit risks which potentially facilitate financial inclusion. However, Fintech lenders might expand market share by exploiting the current GSEs' underwriting and securitization setup.

Though it appears that technology may have been used to serve lenders' own interests, potentially at the cost of the borrowers or other lenders, this paper does not imply how the future use of technology in mortgage market and more broadly, consumer credit markets would evolve. As more investment being made at both deposit taking and non-deposit taking institutions, it is likely that borrowers with different characteristics gain or loss disproportionately. A thorough evaluation of consumer welfare and social welfare under such circumstance is needed for regulation purpose.

Appendix A

Tables

Table A.1: Summary Statistics.

	All	Traditional lenders	Fintech lenders
FICO	752.6083	754.0361	741.7758
	(45.1445)	(44.3593)	(49.3803)
LTV	71.8478	72.0466	70.3399
	(17.3640)	(17.4327)	(16.7570)
Interest rate	4.0217	4.0103	4.1079
	(0.6007)	(0.6009)	(0.5929)
Loan amount ($1,000)	233.0873	234.5648	221.8773
	(126.6393)	(126.8434)	(124.5104)
Term (in months)	308.3316	310.1751	294.3444
	(81.7107)	(80.7438)	(87.4476)
Risk layers	0.8805	0.8607	1.0306
	(0.7826)	(0.7753)	(0.8200)
Cash-out refinance flag	0.2741	0.2586	0.3922
	(0.4461)	(0.4378)	(0.4882)
Investment purpose flag	0.0798	0.0819	0.0640
	(0.2709)	(0.2741)	(0.2448)
DTI above 45 flag	0.0715	0.06951	0.8649
	(0.2576)	(0.2543)	(0.2811)
One borrower flag	0.4551	0.4507	0.4878
	(0.4980)	(0.4976)	(0.4999)
Brokeraged loan flag	0.1032	0.1048	0.0903
	(0.3042)	(0.3064)	(0.2866)
Observations	8,691,496	7,679,344	1,012,152

Notes. This table presents loan-level summary statistics for the full sample and subsamples of loans originated by traditional lenders and Fintech lenders separately. The sample includes all GSEs fixed rate, single family loans whose lenders are identified and are originated between June 2011 and December 2018. All table entries represent sample means or, in parentheses, standard deviations. See Section 2 for further details on data sources and sample construction.

Table A.2: Fintech lenders selection on GSE grid cell of credit score and LTV

	(1) Fintech	(2) Fintech
FICO	-0.001240***	-0.001209***
	(0.000033)	(0.000055)
LTV	-0.009535***	-0.009408***
	(0.000289)	(0.000516)
FICO × LTV	0.000011***	0.000011***
	(0.000000)	(0.000001)
State trend FE	Yes	No
Zip-3 FE	No	Yes
Year-month FE	No	Yes
Observations	8,691,496	8,691,469
Adjusted R-squared	0.0436	0.0449

Notes. This table reports the results of a loan-level linear probit model regressing whether the lender is a Fintech lender on LTV, FICO and the interaction term, as specified in Equation 4.1. Column (1) includes state-by-time fixed effects and Column (2) include 3-digit zipcode fixed effects and origination month fixed effects. Standard errors are clustered at state-year-month level or 3-digit zipcode level and reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table A.3: Differences in loan risks for traditional lenders and Fintech lenders.

Panel A: Forecasting models for loan outcome using observables.

	(1) 90+ days delinquent	(2) Default	(3) Prepaid
Interest rate	0.0911***	0.1075***	0.5331***
	(0.0071)	(0.0092)	(0.0077)
Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
FICO-LTV Grids	Yes	Yes	Yes
Observations	5,910,322	5,910,322	5,910,322
Adjusted R-squared	0.149	0.135	0.0737

Panel B: Difference in actual loan outcomes conditional on predicted outcomes.

	(1) 90+ days delinquent	(2) Default	(3) Prepaid
Fintech	0.0000	0.0002	0.0192***
	(0.0002)	(0.0001)	(0.0045)
Predicted probabilities	0.9679***	0.9398***	1.0358***
	(0.0157)	(0.0154)	(0.0193)
Fintech × Predicted probabilities	-0.0640	0.0553	0.2523***
	(0.0415)	(0.0551)	(0.0192)
Observations	5,910,322	5,910,322	5,910,322
Adjusted R-squared	0.0172	0.00813	0.0948

Notes. Panel A reports the results of a loan-level probit model regressing whether the loan was 90+ days delinquent (Column (1)), default (Column (2)) and prepaid (Column (3)) in 36 months after origination on observables including interest rate, LTV, FICO, Risk layers (specifically, cash-out refinance flag, investment purpose flag, high DTI flag, and one-borrower flag) and other contracting terms at loan origination are used as forecasting variables, as specified in Equation 4.2. All columns include state fixed effects, year-by-month fixed effects and FICO-LTV grid fixed effects. Panel B reports the results of a loan-level OLS model regressing whether the loan was 90+ days delinquent (Column (1)), default (Column (2)) and prepaid (Column (3)) in 36 months after origination on an indicator for whether the loan is originated by a Fintech lender, predicted delinquent, default or prepaid probabilities, and interaction terms, using estimates from Panel A. Standard errors are clustered at state-year-month level and reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table A.4: Fintech lenders selection on risk layers.

	(1) Fintech	(2) Fintech	(3) Fintech	(4) Fintech
Risk layers	0.0142***	0.0151***		
	(0.0022)	(0.0022)		
Cash-out refinance flag			0.0444***	0.0432***
			(0.0063)	(0.0062)
Investment purpose flag			-0.0311***	-0.0275***
			(0.0037)	(0.0031)
DTI above 45 flag			0.0077***	0.0079***
			(0.0013)	(0.0013)
One borrower flag			0.0068***	0.0083***
			(0.0011)	(0.0011)
FICO	-0.0004***	-0.0004***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LTV	0.0004*	0.0003	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Brokeraged loan flag	-0.0096**	-0.0104**	-0.0075**	-0.0086**
	(0.0040)	(0.0040)	(0.0036)	(0.0036)
Log loan amount ($1,000)	-0.0001	0.0041**	-0.0046*	-0.0015
	(0.0018)	(0.0017)	(0.0023)	(0.0020)
Log term (in years)	-0.0785***	-0.0764***	-0.0706***	-0.0693***
	(0.0070)	(0.0067)	(0.0056)	(0.0054)
State trend FE	Yes	Yes	Yes	Yes
FICO-LTV Grids	Yes	Yes	Yes	Yes
Observations	8,691,496	8,691,469	8,691,496	8,691,469
Adjusted R-squared	0.0542	0.0551	0.0572	0.0577

Notes. This table reports the results of a loan-level linear probability model, as specified in Equation 5.1, regressing whether the lender is a Fintech lender on the number of risk layers, which is defined as the sum of four indicator variables: cash-out refinance flag, investment purpose flag, DTI above 45 flag, and one borrower flag. Control variables include FICO, LTV, brokeraged loan flag, loan amount, and loan term. All columns include state-by-time fixed effects, and FICO-LTV grid fixed effects. Standard errors are clustered at the FICO-LTV grid level and reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table A.5: Fintech lenders pricing on risk layers.

	(1) Interest rate	(2) Interest rate
Fintech	0.1163***	0.1152***
	(0.0214)	(0.0223)
Risk layers = 1	0.0596***	0.0562***
	(0.0021)	(0.0020)
Risk layers = 2	0.2064***	0.2001***
	(0.0066)	(0.0064)
Risk layers = 3	0.3847***	0.3740***
	(0.0122)	(0.0120)
Risk layers = 4	0.5513***	0.5366***
	(0.0101)	(0.0095)
Fintech × Risk layers = 1	-0.0082	-0.0067
	(0.0054)	(0.0057)
Fintech × Risk layers = 2	-0.0766***	-0.0742***
	(0.0187)	(0.0192)
Fintech × Risk layers = 3	-0.1628***	-0.1606***
	(0.0315)	(0.0320)
Fintech × Risk layers = 4	-0.1510***	-0.1492***
	(0.0312)	(0.0318)
Controls	Yes	Yes
State trend FE	Yes	No
Zip-3 FE	No	Yes
Year-month FE	No	Yes
FICO-LTV Grids	Yes	Yes
Observations	8,691,496	8,691,469
Adjusted R-squared	0.765	0.766

Notes. This table reports the results of a loan-level OLS model regressing whether interest rate on Fintech indicator, groups of risk layers, and the interaction terms, as specified in Equation 5.2. Control variables are included as in A.4. Column (1) includes state-by-time fixed effects and Column (2) include 3-digit zipcode fixed effects and origination month fixed effects. Standard errors are clustered at lender level and reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table A.6: Differences in loan risks by risk layers.

	(1) 90+ days delinquent	(2) Default	(3) Prepaid
Fintech	-0.0002	0.0002*	0.0791***
	(0.0002)	(0.0001)	(0.0105)
Risk layers = 1	0.0031***	0.0017***	-0.0108***
	(0.0002)	(0.0001)	(0.0012)
Risk layers = 2	0.0060***	0.0032***	-0.0152***
	(0.0003)	(0.0002)	(0.0027)
Risk layers = 3	0.0043***	0.0020***	-0.0470***
	(0.0005)	(0.0003)	(0.0058)
Risk layers = 4	0.0042***	0.0011	-0.0714***
	(0.0011)	(0.0007)	(0.0070)
Fintech × Risk layers = 1	-0.0009***	-0.0002	0.0158***
	(0.0003)	(0.0001)	(0.0021)
Fintech × Risk layers = 2	0.0005	0.0010***	0.0436***
	(0.0005)	(0.0003)	(0.0038)
Fintech × Risk layers = 3	0.0009	0.0016***	-0.0135
	(0.0010)	(0.0004)	(0.0100)
Fintech × Risk layers = 4	0.0047***	0.0047***	-0.0227***
	(0.0015)	(0.0012)	(0.0084)
Interest rate	0.0023***	0.0012***	0.1484***
	(0.0002)	(0.0001)	(0.0099)
Controls	Yes	Yes	Yes
State trend FE	Yes	Yes	Yes
FICO-LTV Grids	Yes	Yes	Yes
Observations	5,910,322	5,910,322	5,910,322
Adjusted R-squared	0.0153	0.00681	0.0953

Notes. This table reports the results of a loan-level linear probability model regressing whether the loan was 90+ days delinquent (Column (1)), default (Column (2)) and prepaid (Column (3)) in 36 months after origination on Fintech indicator, groups of risk layers, and the interaction terms. Control variables are included as in A.4. All columns include state-by-time fixed effects and FICO-LTV grid fixed effects. Standard errors are clustered at lender level and reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table A.7: TBA price loadings on Fintech share and treasury rate.

	(1) TBA price	(2) TBA price	(3) TBA price
Fintech share	-0.0138	-0.2348	-0.0056
	(0.0578)	(0.1767)	(0.0457)
10-year treasury rate	-4.0037***		
	(0.2858)		
Fintech share × 10-year treasury rate	0.0131	0.0899	0.0037
	(0.0254)	(0.0559)	(0.0143)
Year-month FE	No	Yes	Yes
Coupon rate FE	Yes	No	Yes
Maturity FE	Yes	No	Yes
Observations	1,261	1,263	1,261
Adjusted R-squared	0.849	0.111	0.884

Notes. This table reports the results of an OLS model regressing the TBA price on corresponding Fintech share, 10-year treasury rate and their interaction term. Each observation is at the year-month, coupon rate and maturity level. TBA price is the average close price for TBA contracts with a given coupon rate and maturity level. Fintech share is the aggregate share of assets originated by Fintech lenders for all TBA-elegible MBS securities with a given issuance month. Column (1) includes coupon rate fixed effects and maturity fixed effects. Column (2) includes year-month fixed effects. Column (3) includes all above fixed effects. Standard errors are clustered at coupon rate-maturity level and reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix B

Figures

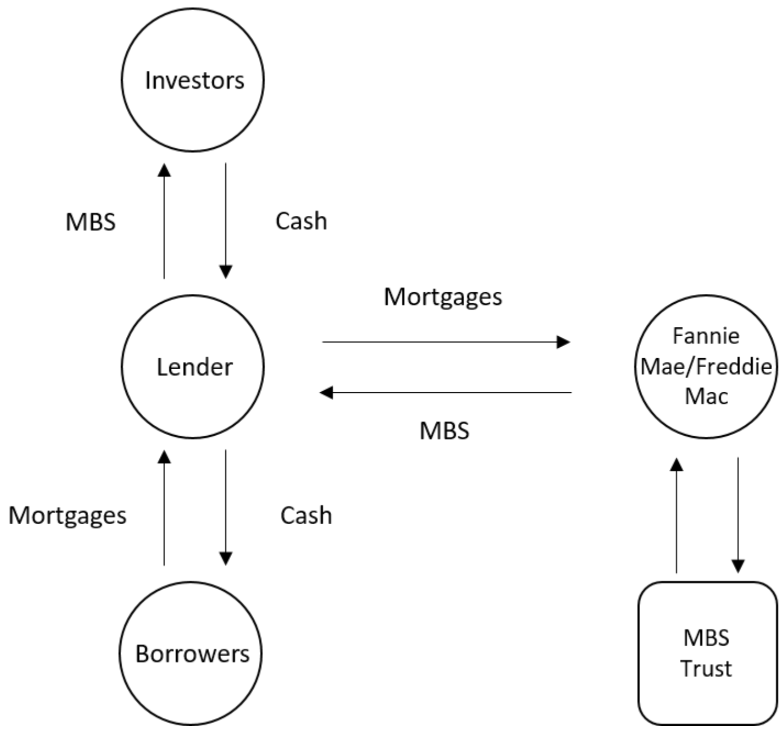


Figure B-1: Illustration of a lender swap transaction.

Note: The figure illustrates how different parties (namely, MBS investors, mortgage lenders, mortgage borrowers, and GSEs) are involved in a common securitization process, the lender swap transaction.

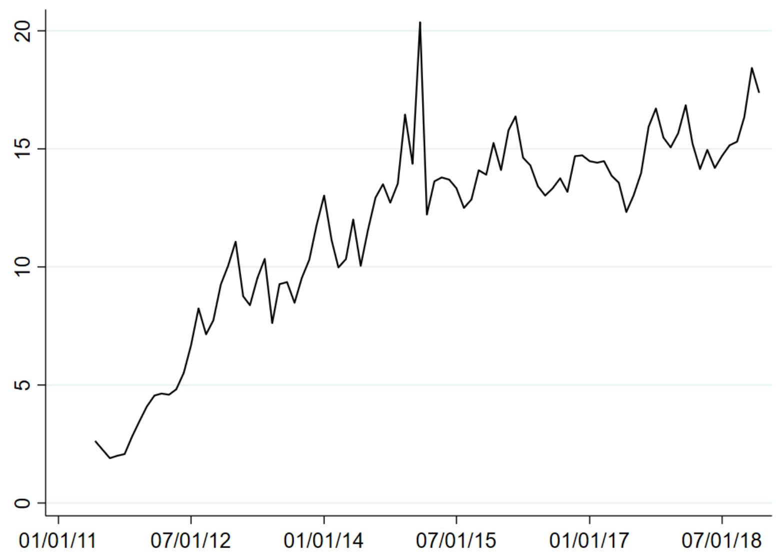


Figure B-2: Fintech mortgage lenders origination shares by month.

Note: Fintech mortgage lenders are online and centralized processing mortgage firms, as classified in Buchak et al (2018). Each point is the Fintech mortgage lenders origination share as a fraction of total origination in the same month for the sample of GSE-acquired, lender-identified mortgages between June 2011 and December 2018, as described in Section 2.

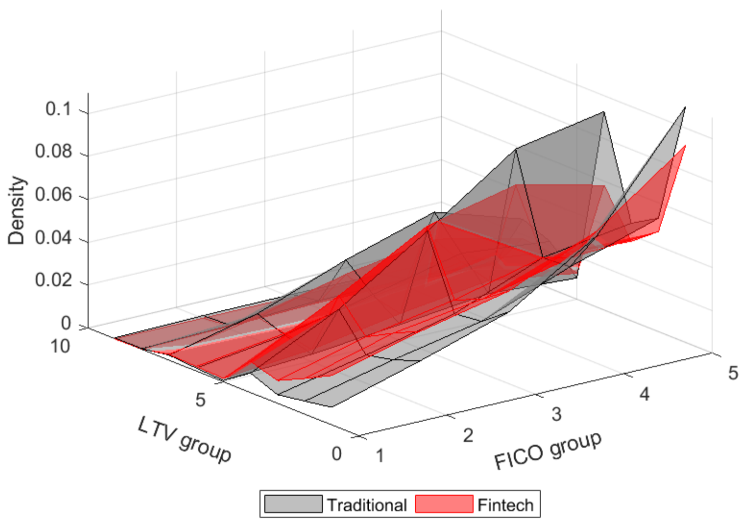
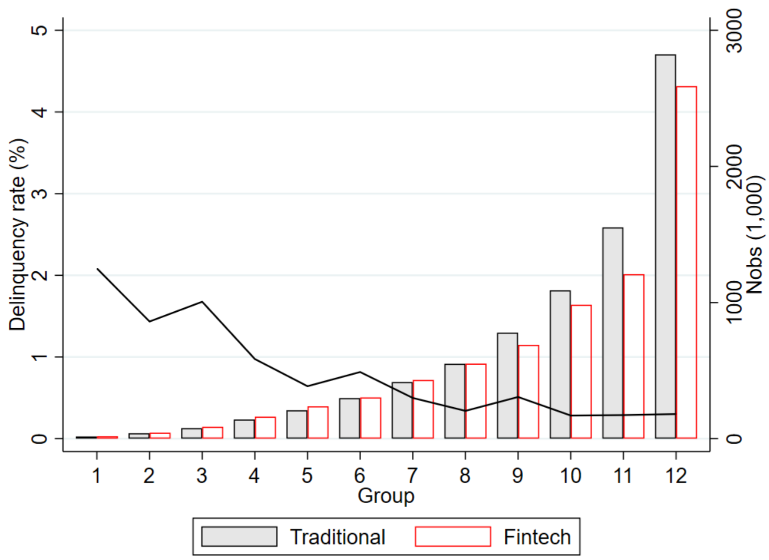


Figure B-3: Joint distribution of FICO and LTV for traditional and Fintech lenders.

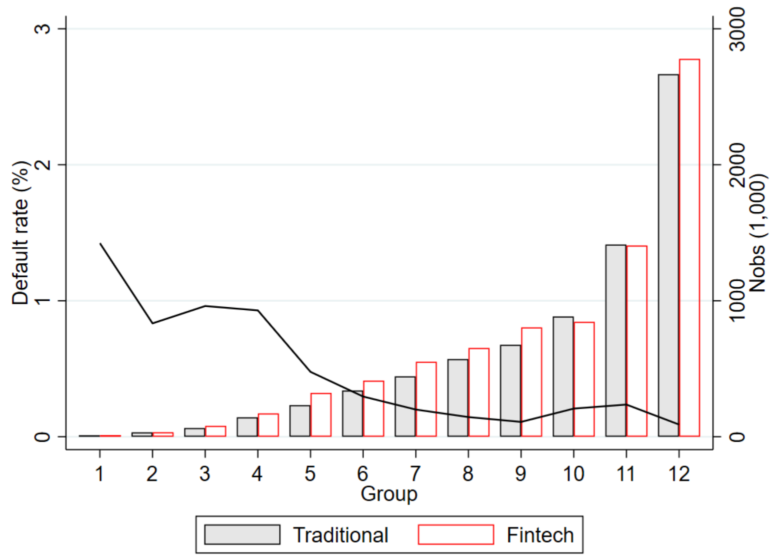
Note: This figure plots the distribution of FICO-by-LTV groups for traditional and Fintech lenders respectively. FICO group 1 to group 5 are defined accordingly by [620,660), [660,700), [700,740), [740,780], [780,850]. LTV group 1 to group 9 are defined accordingly by (0,60], (60,70], (70,75], (75,80], (80,85], (85,90], (90,95], (95,97], and (97,105].



	Predicted delinquency rate (%) range	Traditional lenders	Fintech lenders	t-test
1	(0,0.05]	0.0263	0.0300	0.7082
2	(0.05,0.1]	0.0664	0.0731	0.6517
3	(0.1,0.2]	0.1285	0.1455	1.3020
4	(0.2,0.3]	0.2347	0.2694	1.5537
5	(0.3,0.4]	0.3478	0.3965	1.4954
6	(0.4,0.6]	0.4964	0.5047	0.2506
7	(0.6,0.8]	0.6929	0.7187	0.5291
8	(0.8,1.0]	0.9167	0.9188	0.0324
9	(1.0,1.5]	1.2980	1.0115	**2.4090**
10	(1.5,2.0]	1.8162	1.6396	**1.8595**
11	(2.0,3.0]	2.5867	2.0139	**5.3785**
12	(3.0,100]	4.7056	4.3163	**2.9598**

Figure B-4: Actual 90+ days delinquency rate for traditional and Fintech lenders by predicted delinquency rate groups.

Note: This figure plots actual 90 and plus days delinquency rate within 3 years since origination for traditional and Fintech lenders separately by predicted delinquency groups using observables only. Predicted delinquency rate are calculated from probit regressions of actual delinquency outcome on risk layer groups, interest rate and all control variables as in B-6, as specified in Equation 5.1 and reported in Table A.3 Panel A. Loans are separated into 12 groups based on the predicted delinquency rate from low to high. Each bar represents the actual delinquency rate in that group on the x-axis for traditional lenders and Fintech lenders accordingly. The number of loans in each group is also plotted on the right y-axis. The table reports the t-test statistic for the difference in delinquency rates for traditional and Fintech lenders. P-values that indicate significance at 10% level are marked in bold.



	Predicted default rate (%) range	Traditional lenders	Fintech lenders	t-test
1	(0,0.025]	0.0109	0.0122	0.3915
2	(0.025,0.05]	0.0326	0.0334	0.1236
3	(0.05,0.1]	0.0646	0.0801	**1.7250**
4	(0.1,0.2]	0.1434	0.1720	**2.0938**
5	(0.2,0.3]	0.2329	0.3229	**3.8207**
6	(0.3,0.4]	0.3406	0.4132	**2.0815**
7	(0.4,0.5]	0.4442	0.5515	**2.2565**
8	(0.5,0.6]	0.5715	0.6530	1.3175
9	(0.6,0.7]	0.6763	0.8044	**1.6840**
10	(0.7,1.0]	0.8847	0.8452	0.6483
11	(1.0,2.0]	1.4134	1.4066	0.0994
12	(2.0,100]	2.6667	2.7779	0.7843

Figure B-5: Actual default rate for traditional and Fintech lenders by predicted default rate groups.

Note: This figure plots actual default rate within three years since origination for traditional and Fintech lenders separately by predicted default groups using observables only. Predicted default rate are calculated from probit regressions of actual default outcome on risk layer groups, interest rate and all control variables as in B-6, as specified in Equation 5.1 and reported in Table A.3 Panel A. Loans are separated into 12 groups based on the predicted default rate from low to high. Each bar represents the actual default rate in that group on the x-axis for traditional lenders and Fintech lenders accordingly. The number of loans in each group is also plotted on the right y-axis. The table reports the t-test statistic for the difference in default rates for traditional and Fintech lenders. P-values that indicate significance at 10% level are marked in bold.

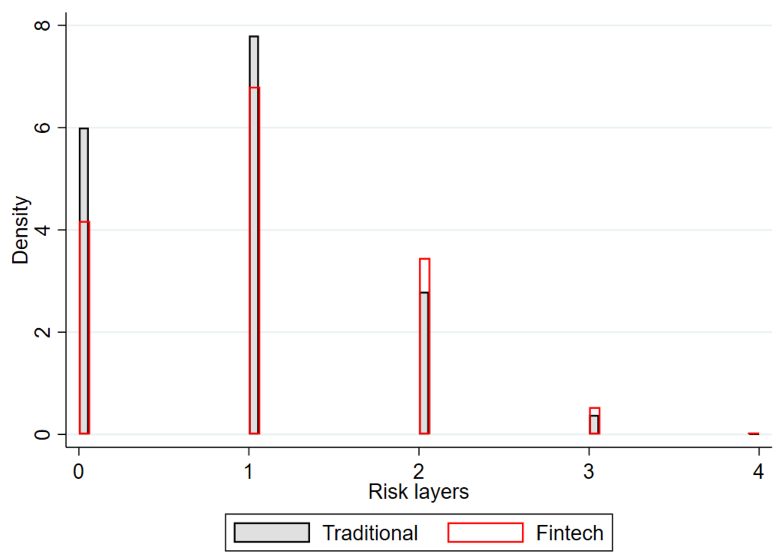
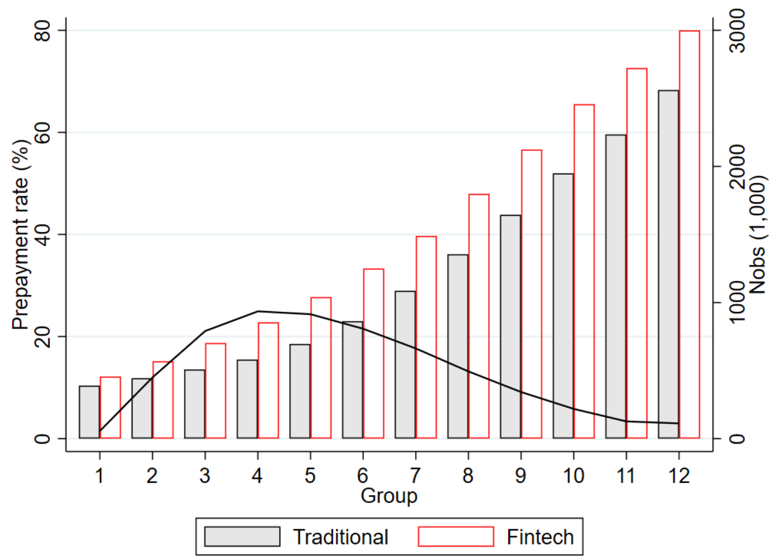


Figure B-6: Distribution of risk layers for traditional and Fintech lenders.

Note: This figure plots the distribution of risk layers groups for traditional and Fintech lenders respectively. Risk layers are defined as the sum of four indicator variables: cash-out refinance flag, investment purpose flag, DTI above 45 flag, and one borrower flag.



	Predicted prepayment rate (%) range	Traditional lenders	Fintech lenders	t-test
1	(0,5]	10.3828	12.1739	**2.3955**
2	(5,10]	11.8430	15.1595	**15.2489**
3	(10,15]	13.5591	18.7381	**36.1157**
4	(15,20]	15.4901	22.7934	**57.1937**
5	(20,25]	18.5473	27.7442	**68.9520**
6	(25,30]	23.0093	33.3362	**68.7309**
7	(30,35]	28.9696	39.7232	**60.7529**
8	(35,40]	36.1337	47.9527	**53.6537**
9	(40,45]	43.8559	56.6347	**45.1459**
10	(45,50]	51.9828	65.5322	**36.6509**
10	(50,55]	59.6049	72.6166	**25.7461**
12	(55,100]	68.3173	80.0057	**20.5026**

Figure B-7: Actual prepayment rate for traditional and Fintech lenders by predicted prepayment rate groups.

Note: This figure plots actual prepayment rate within three years since origination for traditional and Fintech lenders separately by predicted prepayment groups using observables only. Predicted prepayment rate are calculated from probit regressions of actual prepayment outcome on risk layer groups, interest rate and all control variables as in B-6, as specified in Equation 5.1 and reported in Table A.3 Panel A. Loans are separated into 12 groups based on the predicted prepayment rate from low to high. Each bar represents the actual prepayment rate in that group on the x-axis for traditional lenders and Fintech lenders accordingly. The number of loans in each group is also plotted on the right y-axis. The table reports the t-test statistic for the difference in prepayment rates for traditional and Fintech lenders. P-values that indicate significance at 10% level are marked in bold.

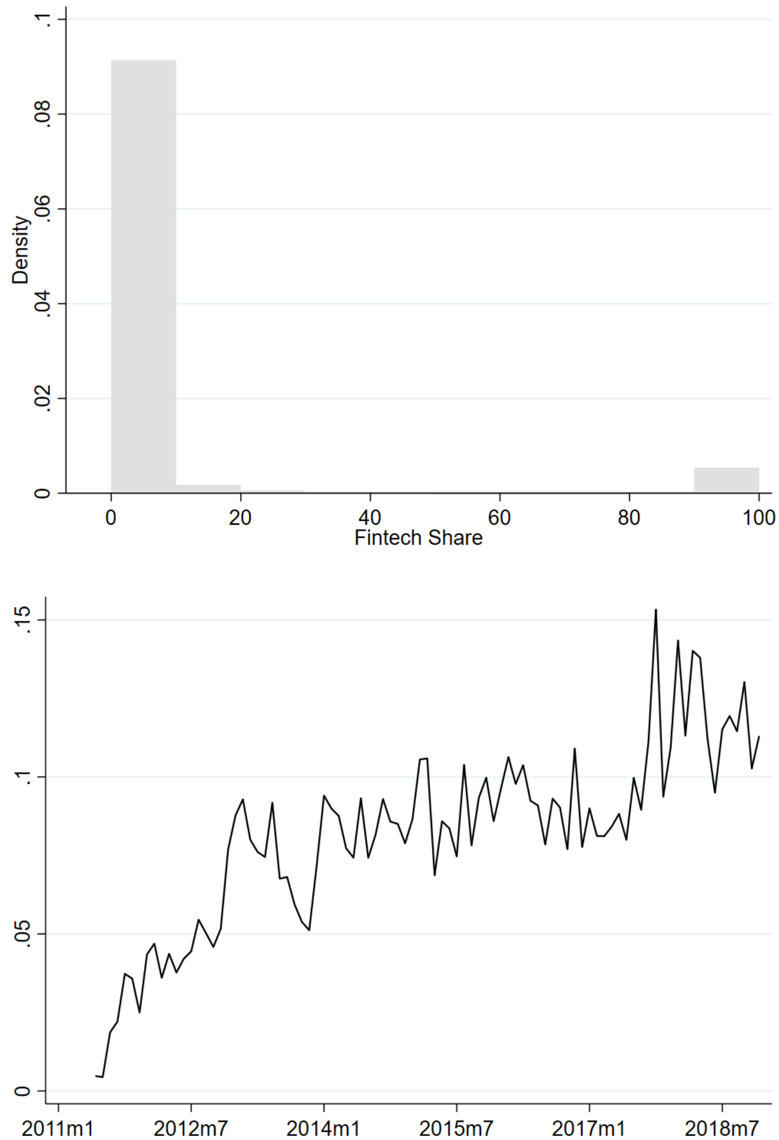


Figure B-8: Fintech shares in MBS and TBA contract.

Note: Graph on the top illustrates the distribution of the share of Fintech loans in a MBS security. Graph on the bottom plots the approximate share of Fintech loans in TBA contracts delivered each month.

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