The Impact of FinTechs in the SFH Mortgage Market

Introduction

The rise of FinTech banks and lending institutions marks a significant shift in the way people interact with financial institutions and their relationship with debt. Initially, FinTech lenders were among the first easy-to-access peer-to-peer lending facilitators, but in the last decade or so, they have started to move into the mortgage market, quickly gaining market traction, to the point where over half of mortgages written today are done so by a FinTech lender. By leveraging big data, FinTech companies streamline mortgage processes, potentially enhancing efficiency and the borrower experience. Moreover, it has been argued that this shift away from traditional brick-and-mortar retail lenders can better serve underserved markets, such as less affluent neighborhoods and racial minorities.

While traditional lenders can collect basic financial information about a potential lendee and evaluate the value of the home fairly consistently, FinTech lenders have access to other complementary education, potentially identifying reliable lenders that may not fit the traditional profile on paper. Since these online lenders will likely continue to grow and eventually force the old guard of lenders to adopt more FinTech-like offerings, it is crucial to understand how they impact the mortgage lending market today. We hypothesize that because FinTech lenders have access to a much larger and more nuanced profile of a potential borrower, they are better able to discriminate between trustworthy borrowers who would make payments on time and without delay than the traditional brick-and-mortar lender.

Literature Review

The potential ability for FinTech lenders to coexist alongside traditional credit lines has already been well-established around the world. Bhattacharya and Chopra (2019) conduct a panel analysis across Indian states over the last 25 years, revealing a significant credit gap between borrowers' demand and the supply offered by traditional lenders. They define six major segments within retail lending and can link larger credit shortages to areas that are more impoverished and less developed. Markara et. al. (2021) look at this along the rural-urban dimension in the United States. In this paper, we examine the role of peer-to-peer (P2P) platforms in enhancing financial inclusion from the borrower’s point of view across the rural-urban dimension. They find that the number of P2P loan requests increases when there are local bank branches in a rural area, since to access most P2P lending services in the US, one needs a bank account in the first place. More pertinently, however, they also identify in urban areas that the number of P2P loan requests is higher when those areas have fewer pawnshops per capita. Therefore, they should know how P2P lending can include rural populations in the large credit system and offer an alternative to those in urban communities.

Regarding the actual power of FinTech companies to ascertain good lenders from bad ones, we look to the Berg et. al. paper. These authors determine the additional information power of a potential borrower's digital footprint to predict consumer default (personal loans). By analyzing data from a German furniture store offering payment plans for these medium-sized purchases, Berg et. al. find that extremely cheaply obtained information such as the device used to log into the site (iOS vs. Android), whether an e-mail address contains the person's name, the email domain (Gmail, Yahoo, Hotmail, etc.), how the customer was directed to the site (search or directed advertisement), among others have information that can exceed that of a private credit scoring service. Moreover, they find that this information is complementary to credit scoring, so the model including both sources of information outperforms either. This paper helps reveal how a home mortgage lender would like to have access to this digital footprint to have a better understanding of a borrower's ability to pay back their mortgage.

The reality of FinTech home mortgage lending is studied by Fuster et. al. (2010). They show, using similar loan-level data as we have, that FinTech lenders process mortgage applications much faster than traditional lenders, even after controlling for observable characteristics. They also show that FinTech loans do not default at a higher rate, which has direct connections to our research question. Also, because FinTech lenders do not have nearly the same frictional or fixed costs, they can adjust their supply more easily to outside demand shocks. Additionally, buyers in areas with more FinTech lending are more likely to refinance their loans in advantageous circumstances (either pulling money out of their homes in a cash-out refinance or lowering their interest rates in a traditional one). However, these authors do not find any evidence that FinTechs are better able to access underserved borrowers.

The final paper we look at is Jagatani et. al (2023), which looks at FinTech lending the era of COVID-19. Since home lending exploded in this period as middle-class Americans started saving much more and looked to enter the homeownership market while interest rates market-wide were quite low. Jagatini finds that the proprietary algorithms that FinTech lenders use can better evaluate trustworthy borrowers from untrustworthy ones. Moreover, she finds that this is not a result of "cream-skimming", that is FinTech lenders are not performing better simply because they are able to pry away to best borrowers from the traditional lenders.

Ideal Research Design

If we had unlimited access to data, we would first collect loan-level data on the following general categories of data:

- Loan Performance Data: Loan-level data is based on origination date, loan amount, interest rates, borrower credit scores, loan-to-value ratios, delinquency status, value of the underlying home. percentage paid as a down payment, balance etc.

- Borrower Demographics: Obtain demographic data of borrowers, including income, employment status, age, education, and geographic location, etc.
- Economic Indicators: Collect macroeconomic data such as housing market trends, unemployment rates, and interest rate changes over the study period.
- Institutional Data: Gather perfect information on the lending institutions themselves particularly their size, market share, business models, risk management practices, and manner of evaluating loan candidates.

We would then use some sort of matching method to collect loans written by traditional banks and FinTech lenders on both the properties of the loan (LTV, interest rates, home value, etc.) and the borrower (income, age, location, education, etc.). With our samples matched all across the country and perhaps bucketed yearly by origination date, we could then look at the spread in default rates across these two groups to ascertain an effect size.

For instance, one of the categories we could match would be married couples with household incomes over 200k a year buying a $1M home in the Austin, TX area in 2013, and look at the difference between those who opted for a FinTech lender over a traditional one. Crucially, we cannot just run an experiment where we instruct certain people to go get a loan from a FinTech/traditional lender, because this removes the loan selection process that both lenders and potential borrowers engage in when shopping for a mortgage. This selection process can dictate the loan outcomes as people look for the most favorable terms.

In our real study, we only really have information in the first category of data, that is the Loan Performance Data in one quarter (2021Q1). This alone left about 1.5M loans to analyze from our two data sources, Freddie Mac and Fannie Mae, which is more than enough for our purposes, but a more robust analysis would include all the information available.

Findings

We take loan-level data from Freddie Mac and Fannie Mae from the 1st quarter of 2021 and combine it with monthly performance data to determine if any of those loans were ever in default. This totals about 1.45 million loans which we have the following complete data for. We look at a few key characteristics: credit scores, the percentage of mortgage insurance someone has, the loan-to-value ratio, the combined loan-to-value ratio, debt to income ratio, the total balance on the loan, interest rate, loan originator, whether the loan was ever in default and the source of the loan (Freddie Mac or Fannie Mae).

Exploratory Data Analysis

Overall, 52.71% of our data comes from Freddie Mac and 47.29% from Fannie Mae. Our dataset has a cumulative 1.38% default rate.

Credit Scores

From the histogram below we can see that credit scores have a left-skewed distribution since the bulk of buyers have very good credit, but credit is capped at a score of 850.

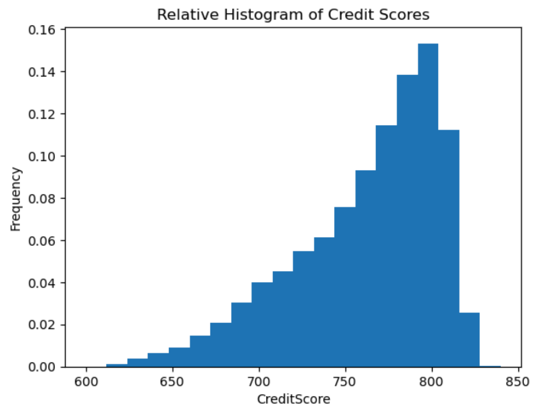

Figure 1. Relative Histogram of Credit Scores

Mortgage Insurance Percentage

From the histograms below we see that the vast majority of lenders do not have Mortgage Insurance at all, and the 17% or so that do typically have about 25-30% of their mortgage insured.

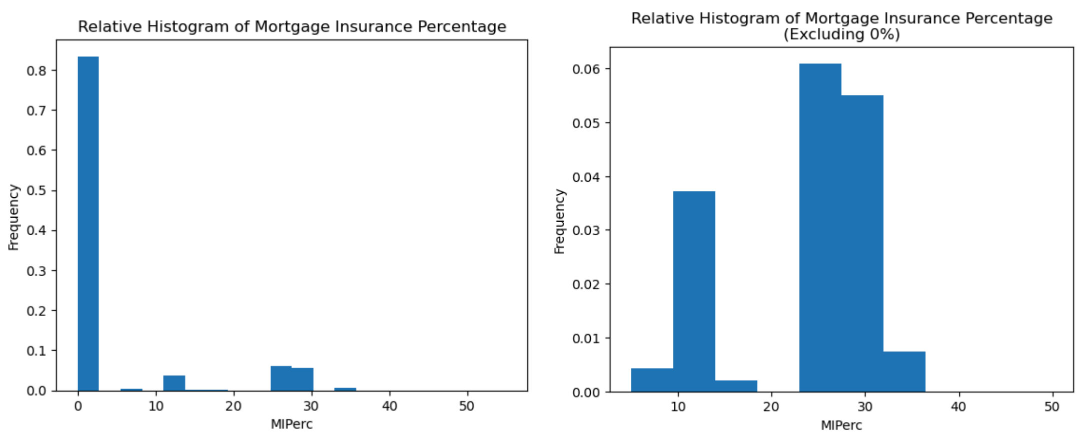

Figure 2.a/b. Relative Histograms of Mortgage Insurance Percentage

(Combined) Loan-to-Value Ratio

The Loan-to-Value ratio is a metric that divides the total balance of this mortgage loan by the total value of the house. The Combined Loan-to-Value ratio is similar but it combines the balance of all mortgages on the price of the house. They mainly differ in situations where people get a shorter-term second mortgage at a higher interest rate when they do not have the cash on have to pay as much as they would like as a down payment. We see a large drop-off at the 80% mark for both variables, indicative of the standard 20% down payment on a house.

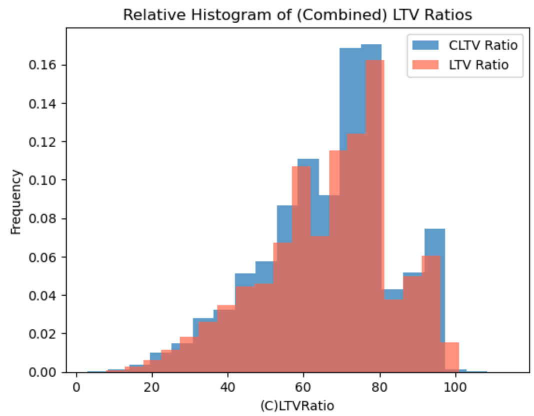

Figure 3. Overlapping Relative Histograms of CLTV and LTV Ratios

Debt-to-Income Ratio

The Debt-to-Income Ratio is the monthly debt payments divided by the borrower's gross monthly income. We see a hard cut-off at 50% since lenders will not approve mortgages if the borrower's monthly income is too low and they are not confident they can reliably pay them.

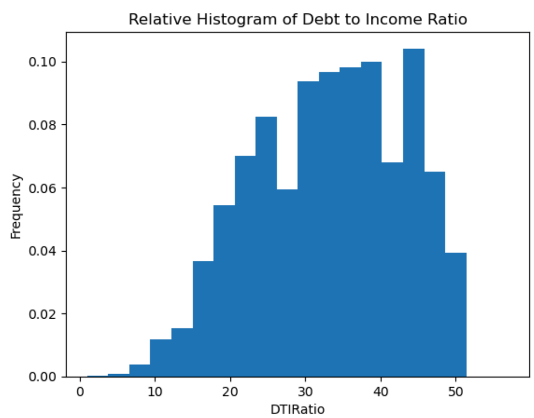

Figure 4. Relative Histograms of DTI Ratio

Interest Rates

We see that interest rates are very clustered around 2.7-2.9% APR. This is reflective of the overall market conditions at the time. Interest rates were set very low by the Fed to get the economy going after the COVID-19-related recession. For homebuyers, this meant borrowing money was comparatively very cheap.

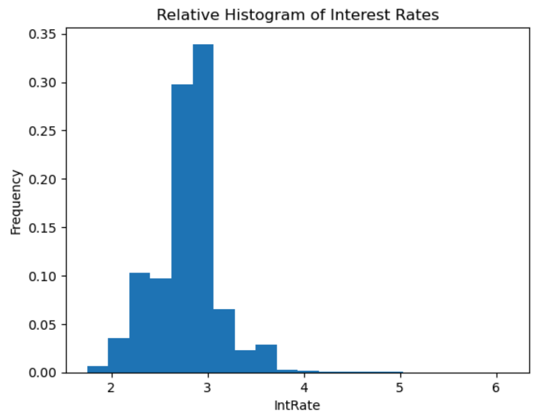

Figure 5. Relative Histograms of Interest Rates

Seller Name

Each of Freddie Mac and Fannie Mae also collect information on the bank or financial institution that sold them the loan in the first place. Each only records explicitly the top 20 institutions by volume, and marks the others in a miscellaneous category. Obviously some of these companies are in the top 20 across both data sources, so we have about 30 unique companies in the dataset. We can see them arranged by loan volume below:

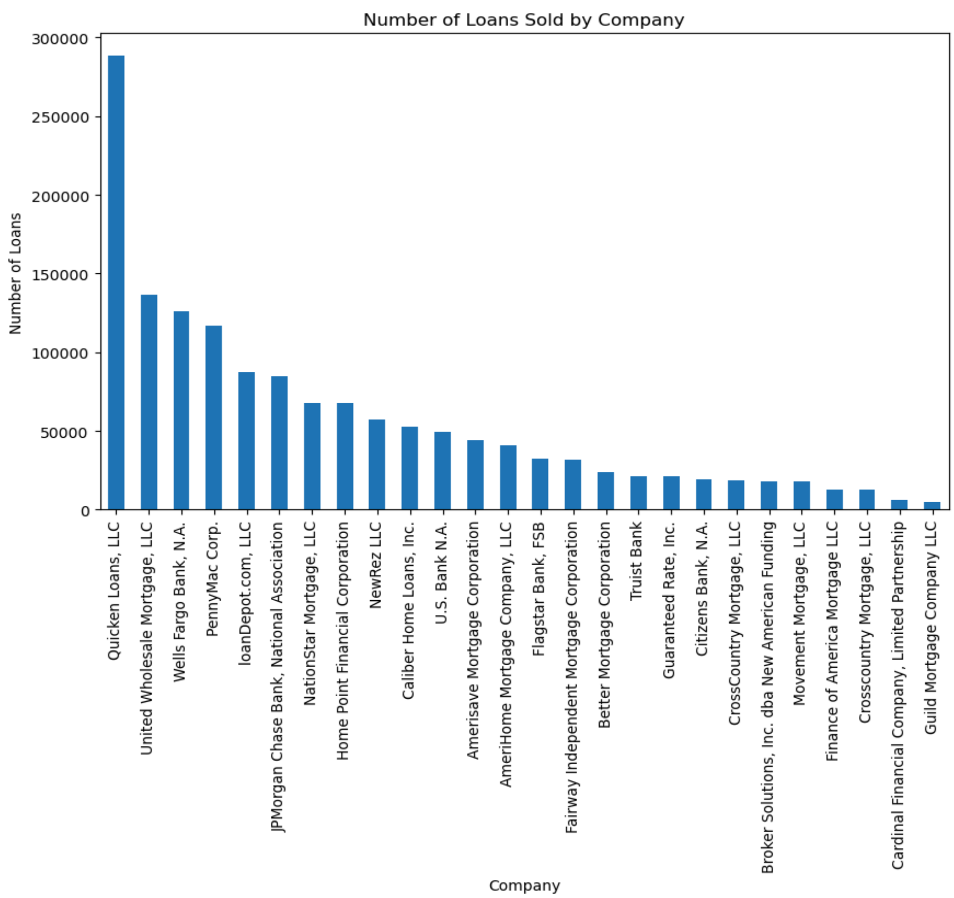

Figure 6. Loan Volume by Company

Tests on Default Rates

Taking inspiration from the Berg et. al. paper, we can use z-tests to show how these various variables affect default rates without needing to use regression. More specifically, we divide up our various numerical variables into quantiles, establish the 0th quantile as the baseline group, and then use z-tests to show that the differences in default rates across groups were statistically significant. Normal linear regression might be difficult given that loan defaulting is a binary outcome variable. We predict 4 of our most important variables: CLTV Ratio, DTI ratio, credit scores, and interest rates:

CLTVRatio

Group	Default Rate	Count	Z-Statistic	P-Value
Quintile 0	0.70%	308294	Baseline	
Quintile 1	0.95%	296371	10.7804	<1e-10***
Quintile 2	1.20%	271220	19.6094	<1e-10***
Quintile 3	1.53%	333179	31.3192	<1e-10***
Quintile 4	2.73%	249991	59.8887	<1e-10***

DTIRatio

Group	Default Rate	Count	Z-Statistic	P-Value
Quintile 0	0.66%	319982	Baseline	
Quintile 1	1.00%	305871	14.7316	<1e-10***
Quintile 2	1.46%	283927	30.6107	<1e-10***
Quintile 3	1.95%	295306	45.0536	<1e-10***
Quintile 4	1.99%	253969	45.2096	<1e-10***

CreditScore

Group	Default Rate	Count	Z-Statistic	P-Value
Quintile 0	3.45%	296134	Baseline	
Quintile 1	1.52%	297157	-47.6970	<1e-10***
Quintile 2	0.87%	285551	-67.3604	<1e-10***
Quintile 3	0.57%	300226	-79.6238	<1e-10***
Quintile 4	0.42%	279987	-82.5084	<1e-10***

IntRate

Group	Default Rate	Count	Z-Statistic	P-Value
Quintile 0	0.82%	345928	Baseline	
Quintile 1	1.11%	428278	12.8757	<1e-10***
Quintile 2	1.42%	290445	23.0137	<1e-10***
Quintile 3	1.65%	139640	25.5463	<1e-10***
Quintile 4	2.41%	254764	50.2024	<1e-10***

Table 1. z-Tests for Difference of Means in Quantiles for CLTV Ratio, DTI Ratio, Credit Scores, and Interest Rates

We can also extend this logic and apply it to all of our companies to see which have statistically significant differences from one another.

SellerName Group	Default Rate	Count	Z-Statistic	P-Value
Quicken Loans, LLC	1.18%	288276	Baseline	
United Wholesale Mortgage, LLC	1.91%	136477	18.6167	<1e-10***
Wells Fargo Bank, N.A.	1.22%	126014	1.0370	0.2997
PennyMac Corp.	1.33%	116858	3.9298	8.50e-05***
loanDepot.com, LLC	1.30%	87342	2.8597	4.2401e-03***
JPMorgan Chase Bank, National Association	0.74%	84878	-10.9109	<1e-10***
NationStar Mortgage, LLC	1.47%	67663	5.9905	2.09e-09***
Home Point Financial Corporation	1.52%	67632	7.1322	9.88e-13***
NewRez LLC	2.26%	56999	20.2368	<1e-10***
Caliber Home Loans, Inc.	1.41%	52442	4.3387	1.43e-05***
U.S. Bank N.A.	1.55%	49549	6.7491	1.49e-11***
Amerisave Mortgage Corporation	1.47%	44223	5.1089	3.24e-07***
AmeriHome Mortgage Company, LLC	1.48%	41151	5.0864	3.65e-07***
Flagstar Bank, FSB	1.86%	32220	10.3972	<1e-10***
Fairway Independent Mortgage Corporation	1.51%	31717	5.0919	3.55e-07***
Better Mortgage Corporation	1.49%	23836	4.1599	3.18e-05***
Truist Bank	0.93%	21159	-3.3607	7.78e-04***
Guaranteed Rate, Inc.	1.30%	21132	1.5274	0.1267
Citizens Bank, N.A.	0.81%	19235	-4.6680	3.04e-06***
CrossCountry Mortgage, LLC	1.22%	18504	0.3986	0.6902
Broker Solutions, Inc. dba New American Funding	1.09%	18095	-1.1435	0.2528
Movement Mortgage, LLC	1.17%	17704	-0.0999	0.9204
Finance of America Mortgage LLC	1.33%	12905	1.4540	0.1459
Crosscountry Mortgage, LLC	1.51%	12693	3.3396	8.39e-04***
Cardinal Financial Company, Limited Partnership	1.47%	5862	1.9849	0.0472**
Guild Mortgage Company LLC	0.78%	4489	-2.4877	0.0129**

Table 2. z-Tests for Difference of Means for our Loan Originators

Logistic Models

Logistic models are specifically designed for binary classification like we have here. We first classify all the companies above by whether they are FinTech companies or a traditional lender and then try to predict Defaults based on credit scores, mortgage insurance percentage, CLTV ratio, DTI ratio, total loan balance (UPB), interest rates, and whether the originator was a FinTech or not. Specifically, we are looking for the coefficient and the standard error of the final independent variable.

Logit Regression Results

Dep. Variable:	DefaultFlag	No. Observations:	1459055
Model:	Logit	Df Residuals:	1459048
Method:	MLE	Df Model:	6
Date:	Fri, 14 Jun 2024	Pseudo R-squ.:	0.07982
Time:	13:47:23	Log-Likelihood:	-97716.
converged:	True	LL-Null:	-1.0619e+05
Covariance Type:	nonrobust	LLR p-value:	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
CreditScore	-0.0115	7.72e-05	-149.064	0.000	-0.012	-0.011
MIPerc	0.0121	0.001	14.221	0.000	0.010	0.014
CLTVRatio	0.0187	0.001	27.388	0.000	0.017	0.020
DTIRatio	0.0315	0.001	37.762	0.000	0.030	0.033
UPB	3.527e-07	4.93e-08	7.149	0.000	2.56e-07	4.49e-07
IntRate	0.6069	0.017	35.285	0.000	0.573	0.641
FinTech	-0.0597	0.015	-4.107	0.000	-0.088	-0.031

Table 3. Logistic Regression Output for the Default Prediction Model

We can see that the FinTech variable is statistically significant and the sign is negative. This means that a loan written by a FinTech does have a lower probability (more specifically, lower log odds, but lower log odds correspond to a lower probability) of defaulting compared to a non-FinTech lender. If we compute a median effect size here, the median loan written by a FinTech lender defaults about 0.05% less of the time than the same loan written by a non-Fintech lender, so even though this finding is statistically significant, we question how economically significant that value is.

Reflection

Finding the true effect size (if there is one) of FinTech lending on default rates is difficult because of the current nature of the mortgage lending market. Each of these data sources only reports by name the 20 largest lenders that sell them loans, but many FinTech lenders like SoFi, Ally, or PNC Bank would not be pushing that many mortgages to be named explicitly. We argue that it is likely that much of the effect size is “lost” to this data reporting, and therefore, we do not believe it possible that we could find much of an effect size using this method. Moreover, many of the companies listed there are not FinTech companies, but they also are not traditional retail banks either. Many of these seem to straddle the line between the two, being affiliated with many independent lenders who sell them mortgages, and wholesale them to Fannie Mae and Freddie Mac. We simply need data from sources we know are firmly in one camp or another so we can be confident about our classification of companies.

Given more time and resources, we would have liked to incorporate some more variables on the overall health of the economy, such as the unemployment rate and overall interest rates, and certainly used data across various quarters of US data. Each of our data sources has data going back every quarter to 1999, through the Great Recession when default rates were closer to 7 or 8%. The cleaning process was just so time-intensive that it seemed unfeasible to do this for another quarter. Even with just one quarter, we had so much data that almost any statistics came up as statistically significant since the standard errors would be getting divided by such large numbers. Additionally, we would have liked to run more robustness and model specification tests on the model. The overall fit was quite low, which we expected, since if it were possible to predict loan defaults with any real degree of confidence using just a handful of variables, someone would have figured out a way to enrich themselves off that knowledge until the effect size was not discernible anymore.