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ABSTRACT

We analyze the costs and benefits of intermediaries for government-sponsored enterprise (GSE) mortgages using regulatory data. We find evidence of lenders pricing for observable and unobservable default risk independently from the GSEs. We then develop and estimate a model of competitive lending in which lenders have skin-in-the-game. Lenders reduce costs by acquiring information beyond the GSEs' criteria but charge markups. On net, interest rates are higher compared to a counterfactual in which the GSEs' criteria are implemented passively. In an extension, the observed differences between banks and nonbanks are more consistent with differences in their skin-in-the-game rather than screening quality.

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1 Introduction

Mortgage debt is by far the largest component of household debt in the U.S., accounting for more than 70% of the $16.5 trillion in household liabilities (Federal Reserve Bank of New York (2022)). Access to mortgage credit significantly depends on the prevailing credit profiles in the mortgage market segment supported by the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac, which comprises the majority of originations since the financial crisis.[1] In this market segment, access to credit depends on two factors: the GSEs' underwriting criteria as implemented through their respective automated underwriting systems (Desktop Underwriter for Fannie Mae and Loan Prospector for Freddie Mac) and potential additional restrictions or "overlays" imposed by private mortgage lenders, which serve as intermediaries by originating the loans that the GSEs eventually securitize.[2]

Considering that the GSEs provide insurance against mortgage default risk and the progress made on the automated underwriting systems, a critical question arises: What extra value do intermediaries' discretionary overlays and pricing of mortgages offer? We specifically focus on a trade-off in which intermediaries can reduce the cost of lending by screening out borrowers who are more likely to default relative to their easily observed risk characteristics (such as credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio), but they also charge markups. We study the welfare of different types of borrowers under the current arrangement versus a counterfactual setting in which the discretionary behavior of intermediaries is eliminated.

We study the trade-off between better screening and lenders' market power using proprietary regulatory data on all loans acquired by the GSEs during 2016-2017, a period during which we can precisely observe the guarantee fees, or g-fees, that the GSEs charge to

[1] In this paper, "the GSEs" refers to Fannie Mae and Freddie Mac and not any other government-sponsored enterprises.

[2] We focus on the role of intermediaries at loan origination and not subsequent servicing or other investor activity.

insure a loan. We first provide reduced-form evidence that intermediaries price observable and unobservable risk independently of the GSEs. These facts collectively suggest that intermediaries have some skin-in-the-game and perform additional screening. However, we also find evidence of significant markups charged by the lenders. We then develop a model of competitive lending by intermediaries in which lenders perform costly screening but also have market power. We estimate the parameters based on the moments from the reduced form observations and use the model to study the interest rates and denial rates that different type of households would face if we changed the current system to a new one in which GSEs' underwriting criteria are implemented passively.

We start our reduced form analysis by showing that interest rates increase with measures of ex-ante observable default risk. We define observable risk as the probability of default predicted by a borrower's credit score, LTV ratio, and DTI ratio. We rely on variation of interest rates net of g-fees for loans offered by the same lender and within the same ZIP code and show that a one percentage point increase in observable risk is associated with a 4.2 basis point increase in interest rates net of g-fees. This result is consistent with lenders having skin-in-the-game, or a positive loss given default, due to the threat of repurchases and exclusion from the GSEs.[3] We also look at the distribution of interest rates as a function of observable risk and find that the gap between the average and the 10th percentile (or between the 90th percentile and the 10th percentile) of interest rates for the safest borrowers is 23 (49) basis points. This gap suggests that GSE intermediaries exploit significant market power. Moreover, we find that the 10th (90th) percentile increases by 1.4 (5.1) basis points for each one percentage point increase in observable risk. The difference between the slope of the average versus the 10th percentile of interest rates as a function of observable risk disciplines the parameters of the model to disentangle between lenders' skin-in-the-game

[3] A "repurchase", sometimes also referred to as a "put-back", refers to when a GSE requires a lender to repurchase a loan based on charges of violating representations and warranties, which can be interpreted as errors in the underwriting process required for delivering a loan to the GSEs. The rate of repurchases increased during the financial crisis but has since remained low. Nevertheless, Goodman (2017) presents evidence that lenders have increased their investment in careful underwriting and imposed overlays to protect themselves against repurchases.

and the correlation between lenders' market power and borrowers' observable risk.

For robustness, we also use data from the National Survey of Mortgage Originators (NSMO) to show that the correlation between interest rates net of g-fees and observable risk is robust to controlling for borrowers' shopping behavior and financial sophistication. We also consider lenders' total origination revenue — instead of the interest rate net of g-fees — and show that the correlation between lender pricing and observable risk is not affected by the use of discount points and lender credits. Origination revenue incorporates a lender's income from selling loans on the secondary market (which is a function of the interest rate on the mortgage) as well as upfront fees, and it does not depend on the distribution of income from these two sources.[4] We also find that our results are robust to controlling for observable prepayment risk, which is a borrower's estimated probability of prepayment as a function of the credit score, LTV ratio, DTI ratio, and loan amount.

We next show that, even after adjusting for observable borrower characteristics, mortgage interest rates net of g-fees are predictive of defaults, which we attribute to residual unobservable risk. In particular, a one percentage point increase in the interest rate net of g-fees is associated with a 47 basis point and statistically significant increase in the default rate conditional on observable risk, which is substantial relative to the overall default rate in the sample of 50 basis points. This result is robust to capturing observable risk via not only credit scores, LTV ratios, and DTI ratios but also an extensive set of characteristics of the borrower (e.g., household demographics), loan (e.g., loan purpose and amount), and property (e.g., value). This result suggests that lenders conduct additional screening beyond these characteristics to determine the risk spread, which could involve improving their risk assessment models or allocating more labor hours to careful loan processing.

For robustness, we show that the correlation between defaults and interest rates is not driven by reverse causation (i.e. the impact of interest rates on delinquencies). We use the variation in interest rates on fixed rate mortgages caused by cross-subsidizations and

[4]We find that the 10th percentile, average, and 90th percentile of origination revenue on average increases by 34 basis points (as a percentage of the loan amount), 44 basis, and 59 basis points, respectively, for each percentage point increase in observable risk.

discontinuities in g-fees and show that the causal impact of interest rate on delinquencies is negligible.[5]

Finally, we also investigate the extensive margin using loan application data. Even when restricting to applications that are accepted by the GSEs' automated underwriting systems, lenders' likelihood to deny an application increases by 1.92 percentage points for each one percentage point increase in observable risk.

Equipped with the above empirical findings, we develop and estimate a model of imperfectly competitive mortgage lending with costly screening technology that explains these observations. We then leverage the model to extract insights about the costs and benefits of intermediaries in the GSE segment of the mortgage market. The model has three key ingredients. First, motivated by evidence of lenders pricing for observable—and unobservable—risk, lenders in the model face a positive expected loss given default. Second, motivated by evidence of lenders also pricing for default risk that is not captured by observable risk characteristics, lenders in the model can implement further screening. Third, lenders can charge markups due to limited shopping by borrowers (Woodward and Hall (2012), Alexandrov and Koulayev (2018)).

Specifically, in the model, we focus on mortgages that are acceptable to the GSEs. Lenders engage in costly screening to draw a signal correlated with consumers' default risk, which affects lenders' costs since they retain a positive expected loss given default. Based on the estimated risk of default, lenders determine which consumers to deny and the cost of lending for consumers they accept. Lenders can also charge markups since consumers shop at a limited number of lenders and choose one, or forgo taking out a mortgage at all, based on a combination of lenders' interest rate offers and idiosyncratic preference shocks. Lenders determine their interest rate offers and how much to screen by maximizing expected profits.

We leverage the model to compare the status quo, in which lenders exercise discre-

[5] The association between defaults and lender pricing is also robust to using origination revenue instead of the interest rate net of g-fees.

tionary overlays and pricing, to a counterfactual in which lenders passively implement the requirements of the GSEs with competitive pricing. That is, in this counterfactual, all applications that are accepted by the GSEs' underwriting criteria are offered a loan with a zero-profits interest rate conditional on the borrower's observable risk.[6] The results of our estimation suggest that, absent intermediaries' screening, the amount of delinquencies would approximately double, which would increase the marginal cost of borrowing by 30% on average over different levels of observable risk. However, this benefit is outweighed by the average 20 basis point markup charged by the intermediaries. Our estimations suggest that switching to passive lending would decrease the average interest rates for the borrowers in the bottom (top) decile of observable risk by 20 (15) basis points.

While the primary question of this paper concerns the costs and benefits of intermediaries in general, an extension of the model with heterogeneous lenders speaks to observed differences between bank and nonbank lenders of GSE loans. In recent years, nonbanks' market share of GSE loans grew from 17% in 2011 to 42% in 2017. This growth not only affects the lending behavior of nonbanks themselves, but it also has important implications for the pricing and lending decisions of banks. Consistent with Buchak et al. (2018), Kim et al. (2018), and Kim et al. (2022), we observe that nonbanks are associated with greater observable risk and greater interest rates conditional on observable risk. But more importantly, we find that as the market share of nonbanks increased over time, they exhibited increasingly higher ex-post defaults. For example, the difference in two-year default rates of nonbanks compared to banks, conditional on observable characteristics, grew from 7.2 basis points in 2013 to 19.4 basis points by 2017.

An extension of the model with heterogeneous lenders suggests that the observed differences between banks and nonbanks are more consistent with fundamental differences in their expected loss given default rather than either type of lender having any screening ad-

[6] In Section 5.3 we discuss how the counterfactual could in principle be implemented by a combination of removing put-back risks and standardizing mortgage applications through a platform that verifies borrowers' information, determines their eligibility for GSE loans, and disseminates the anonymous borrower information to a large number of lenders.

vantage. In particular, the observation that nonbanks are associated with higher observable risk and higher default rates, conditional on observable risk, is consistent with them having a lower expected loss given default. By contrast, differences in screening costs generate a smaller and opposite correlation between observable and unobservable risk. A lower loss given default and a higher screening cost both cause lenders to screen less efficiently, resulting in less informative signals about a consumer's default risk. The key difference is that a lower loss given default also allows a lender to charge a lower interest rate conditional on a given signal of a consumer's risk. The lower interest rate attracts more consumers, and this effect becomes more pronounced as observable risk increases.[7] In the model, the increasing market share of nonbanks from 2013 to 2017 can be emulated by supposing that nonbanks exhibited relative reductions in the loss given default and funding costs and became more preferred by consumers.

This paper contributes to three major themes in the literature. First, it discusses determinants and implications of access to credit in the U.S. mortgage market. This body of work focuses, for example, on race and ethnicity (Bhutta, Hizmo, and Ringo (2021), Bartlett et al. (2022), Giacoletti, Heimer, and Yu (2022), and Frame et al. (Forthcoming)), the GSEs' automated underwriting systems (Johnson (2022)), technology (Jiang, Yang, and Zhang (2023)), lender screening (Adelino, Wei, and Zhao (2023)), regulations (DeFusco, Johnson, and Mondragon (2020), Fuster, Plosser, and Vickery (2021)), repurchases and servicing costs (Goodman (2017)), fair pricing and credit allocation by region (Hurst et al. (2016) and Kulkarni (2016)), capacity constraints (Fuster, Lo, and Willen (2017)), and interest rates (Bhutta and Ringo (2021), Bosshardt et al. (Forthcoming)). We contribute by providing evidence that lenders price for risk on GSE loans in a manner that is indepen-

[7] One explanation for the difference in the expected loss given default is that banks more often have an incentive to protect rents from other business lines. By contrast, nonbanks, which typically have a monoline business model, may perceive declaring bankruptcy as a less costly limit on losses. For example, nonbanks exhibited lower rates of repurchases of risky loans they originated during the housing boom. In particular, within the set of 2007 originations that were delivered to Freddie Mac, 1.08% of the loans delivered by banks have been repurchased compared to only 0.65% of the loans delivered by nonbanks. This may have been due to them failing or being sold to banks during the crisis (e.g., Buchak et al. (2018)) and thus not being liable to further penalties from the GSEs. Nonbanks also generally face lower regulatory scrutiny.

dent of the GSEs' g-fees, consistent with an intensive margin of overlays.

Second, this paper contributes to the literature on the role of nonbanks in mortgage lending (Buchak et al. (2018), Kim et al. (2018), Gete and Reher (2020), Kim et al. (2022), Benson, Kim, and Pence (2023), and Buchak et al. (2024)), including fintechs in particular (Fuster et al. (2019), Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021), and Berg, Fuster, and Puri (2022)). Based on our model, we conclude that the observed differences between banks and nonbanks are more consistent with nonbanks having a lower expected loss given default rather than advantages in screening quality.

Third, our study contributes to the literature on competition and financial market outcomes. This literature covers competition among financial intermediaries, including banks versus banks (Egan, Hortaçsu, and Matvos (2017)), banks versus nonbanks (Benetton, Buchak, and Robles-Garcia (2022)), fintechs versus other intermediaries (Di Maggio and Yao (2021)), and algorithmic versus human underwriting processes (Jansen, Nguyen, and Shams (2021)). It also covers the effects of mortgage lender concentration on monetary policy transmission (Scharfstein and Sunderam (2016)) and fees (Buchak and Jørring (2021)), competitive frictions in mortgage relief programs (Agarwal et al. (2022), Amromin and Kearns (2014)), the relationship between competition and underwriting quality (Yannelis and Zhang (2023)), the effects of competition in the business lending market (Beyhaghi, Fracassi, and Weitzner (2022)), the effects of competition on adverse selection (Mahoney and Weyl (2017)), and welfare (Lester et al. (2019)). The paper also contributes to the literature on screening with data acquisition, such as the rise of screening and big data technologies (Farboodi and Veldkamp (2020)). We add to this literature by showing that noncompetitive markups on GSE loans outweigh the cost reduction due to screening, resulting in higher interest rates compared to a counterfactual in which the discretionary behavior of lenders is eliminated.

The rest of the paper is organized as follows. Section 2 describes the institutional background and data. Section 3 provides evidence that lenders charge risk spreads on GSE loans, consistent with an intensive margin of overlays. Section 4 develops and estimates a model in which lenders' discretionary overlays result from conducting additional screening beyond the GSEs' underwriting criteria and retaining positive losses given default. Section 5 compares the estimated model to a counterfactual with passive intermediation and shows that the discretionary behavior of lenders leads to higher interest rates due to substantial markups outweighing the cost-saving benefits of screening. Section 6 extends the analysis to lender types and shows that the observed differences between banks and nonbanks are more consistent with differences in their expected loss given default rather than screening quality. Section 7 concludes.

2 Institutional background and data

2.1 Institutional background

We focus on mortgage loans acquired by the GSEs. Lenders can deliver a conventional (i.e., not government insured) mortgage to the GSEs if the loan amount does not exceed the corresponding conforming loan limit value and the loan is accepted by the GSEs' automated underwriting systems. The GSEs can purchase individual loans for cash, in which case they pool loans into mortgage-backed securities (MBS), or they can also directly swap pools of loans for mortgage-backed securities. The GSEs guarantee investors of the mortgage-backed securities against the default risk of the underlying mortgages.

As payment for the guarantee, the GSEs charge a guarantee fee or g-fee. The g-fee for a loan typically contains an ongoing component, which is charged as an annual rate, and an upfront component, which is charged as a percentage of the loan amount. The ongoing component largely depends on the loan's general product type (such as fixed rate or adjustable rate), whereas the upfront component depends more on the loan's specific risk characteristics. The upfront g-fee is the sum of components described in each GSE's respective matrix.[8] A base component for all loans with terms greater than 15 years depends on the loan-to-value (LTV) ratio and credit score.[9] Other components can depend on features of the loan (such as the loan purpose) or the property (such as the occupancy type), among other factors. Our measure of the total g-fee, expressed as an annualized rate, combines the ongoing and upfront components by converting the upfront component to an annualized rate using the loan's present value multiplier, which is estimated by the loan's guaranteeing GSE based on the expected duration of the loan.

Lenders obtain an origination revenue net of the g-fee, which can be expressed as a percentage of the loan amount. Similar to Zhang (2022), we compute origination revenue as the sum of two components: upfront closing costs and secondary marketing income. Closing costs is measured by origination charges net of lender credits, which we obtain by merging with the recently expanded HMDA data. Secondary marketing income is the present value of the deviation of a loan's interest rate net of g-fees relative to par, similar to the price of financial intermediation in Fuster, Lo, and Willen (2017). We compute it by subtracting the current coupon yield on GSE-guaranteed MBS[10] as of the origination date from the interest rate net of the total g-fee and multiplying by the respective present value multiplier (PVM):[11]

$$\text{secondary marketing income} = (\text{interest rate} - \text{total g-fee} - \text{MBS yield}) * \text{PVM} \tag{1}$$

[8] See https://singlefamily.fanniemae.com/media/9391/display for the most recent matrix for Fannie Mae, which refers to the upfront g-fee as loan-level price adjustments. See https://guide.freddiemac.com/euf/assets/pdfs/Exhibit_19.pdf for the most recent matrix for Freddie Mac, which refers to the upfront g-fee as credit fees. Note that the current matrix no longer coincides with the matrix during the sample period. See https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/GFee-Report-2021.pdf for general information from the Federal Housing Finance Agency g-fee report.

[9] While the upfront g-fee is generally increasing in default risk, it may not price for risk perfectly. In particular, the matrix is consistent with cross-subsidization of relatively risky borrowers (with high LTV ratios and low credit scores) by relatively less risky borrowers (with low LTV ratios and high credit scores). This is not a problem for our analysis, which focuses on the component of interest rates determined by lenders rather than the GSEs.

[10] Data comes from the Bloomberg series "MTGEFNCL".

[11] If we split up the g-fee into the ongoing and upfront components, then this is also equivalent to: secondary marketing income $= (\text{interest rate} - \text{ongoing g-fee} - \text{MBS yield}) * \text{PVM} - \text{upfront g-fee}$.

Our computation of secondary marketing income is slightly different from Fuster, Lo, and Willen (2017) and Zhang (2022) in that we determine the premium relative to par using the loan's guaranteeing GSE's estimated present value multiplier rather than prices in the secondary market. Despite this difference, we find similar aggregate statistics. For example, we find that the average secondary marketing income during 2018 was 3.22% (Table B.2 in Appendix B), which is consistent with the finding in Fuster, Lo, and Willen (2017) that the price of financial intermediation averaged 1.42% during 2008-2014 while also exhibiting an average upward trend of 0.32% per year, assuming a similar trend continued from 2014 to 2018. Also, the average total origination revenue in our sample is 3.98%, which is similar to the average of 4.6% during 2018-2019 reported by Zhang (2022), especially after accounting for the fact that we additionally subtract out the upfront g-fee (which on average is equal to 0.63% in our sample).

We consider how lenders' interest rates and origination revenues vary with observable default risk as well as ex-post defaults conditional on observable risk. In the context of our analysis, default refers to a 90-day delinquency within 2 years of origination. We compute observable risk as the estimated probability of default based on easily observable characteristics, including determinants of the upfront g-fee (credit score and LTV) as well as the debt-to-income (DTI) ratio. Specifically, it is the predicted value of a regression of default (multiplied by 100) on the interaction of credit score bins corresponding to thresholds in the upfront g-fee (less than 620, 620-639, 640-659, 660-679, 680-699, 700-719, 720-739, and 740 or greater), LTV bins corresponding to thresholds in the upfront g-fee (60% or less, 60.01-70%, 70.01-75%, 75.01-80%),[12] and DTI bins corresponding to quintiles.[13] When referring to the credit score for a loan, we use the representative credit score that is used to determine the g-fee. The representative credit score is the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three.

[12]Note that we restrict to loans with an LTV ratio up to 80%, as discussed later in the data description in Section 2.2.

[13]The thresholds defining the DTI bins are as follows: 24.13%, 31.06%, 37.3%, and 43.01%.

In an extension of our analysis, we examine how observable risk, interest rates, and defaults correlate with different types of lenders. In the context of our analysis, banks refers to depositories, nonbanks refers to lenders that are not banks, and fintechs refers to lenders with a mostly online application process. We use the designation of fintechs from Buchak et al. (2018)). Note that all fintechs are nonbanks, so we can further distinguish fintechs from nonbank-nonfintechs in order to have non-intersecting categories.

2.2 Data

We use data from the Mortgage Loan Information System (MLIS), which is a proprietary regulatory dataset at the Federal Housing Finance Agency (FHFA) consisting of all loans acquired by the GSEs.[14] The aggregate results in the tables and figures of this paper do not contain any confidential or personal identifiable information.

For our baseline sample, we focus on originations during 2016-2017. We start in 2016, which is when precise data on g-fees becomes available, and we end at 2017 because we consider 2-year default rates and do not want to extend into the COVID-19 pandemic. For the results regarding origination revenue, we use the sample of originations during 2018, which we merge with the expanded HMDA data to obtain information on origination charges.[15] Note that observable risk in 2018 is computed based on the model estimated from the baseline 2016-2017 sample rather than the 2018 sample to avoid systematic changes in 2-year default rates associated with the COVID-19 pandemic.

We focus on a subsample of loans for which the upfront portion of the g-fee approximately only depends on the LTV ratio and credit score. In particular, we restrict to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-

[14]Note that GSE loans account for more than 90% of the total origination volume of conventional conforming loans meeting analogous sample restrictions to those in our main sample. This fraction is computed using the National Mortgage Database, a representative sample of residential mortgages maintained by the FHFA and the Consumer Financial Protection Bureau.

[15]We implement an exact merge based on the following characteristics: loan amount rounded to the nearest $5,000, interest rate, year, loan purpose, term, and census tract. We omit observations in either dataset which are identical based on these characteristics.

family detached houses. We also exclude high balance loans exceeding the national baseline conforming loan limit, loans with subordinate financing, and loans with an LTV ratio exceeding 80%. Finally, within the resulting set, we restrict to loans where the total upfront g-fee is within 25 basis points of the component determined by LTV and credit score. The last restriction drops about 6% of observations and accounts for cases where there may be other determinants of the g-fee that we cannot precisely observe.

Table B.1 in Internet Appendix B presents summary statistics for the baseline 2016-2017 sample, and Table B.2 presents summary statistics for the 2018 sample. Note that continuous variables are winsorized at 1%.

3 Empirical findings

This section shows that interest rates net of g-fees are positively associated with observable risk and unobservable risk (i.e., default risk conditional on observable risk). It also shows that denials of mortgage applications increase with observable risk.

3.1 Interest rates and observable risk

Figure 1 shows that observable risk is positively associated with interest rates, even after subtracting out the g-fee. Similarly, column (1) of Table 1 shows that interest rates are positively associated with observable risk while also controlling for ZIP code by year-quarter fixed effects and seller by year-quarter fixed effects, where the assignment of year-quarter is based on the origination date and the seller refers to the entity that sold the loan to the GSEs. Column (2) shows that the association is not significantly affected by including additional controls, including loan amount decile indicators and an indicator for full income and asset documentation. Decomposing the components of observable risk, column (3) shows that interest rates are negatively associated with the credit score and positively associated with the loan-to-value (LTV) ratio and the debt-to-income (DTI) ratio. Columns (4) through (6) show that most of these associations are only partially mitigated by subtracting out the total g-fee. Based on the estimate in column (5), a 1 percentage point increase in the ex-ante probability of default is associated with a 4.2 basis point increase in the interest rate net of g-fees.

To compare the pricing for observable risk with other determinants of interest rates, such as markups, Figure 2 shows the average, 10th percentile, and 90th percentile of interest rates net of g-fees as a function of observable risk.[16] To remove fluctuations in interest rates and enable pooling over the sample period, we focus on the spread relative to the best available rates in a given week, as approximated by the 10th percentile of interest rates net of g-fees for the borrowers in the lowest quartile of observable risk for that week. The 10th percentile of this spread at a given level of observable risk plausibly corresponds to the lowest markups.[17] We find that the 10th percentile increases with observable risk at a rate of 1.4 basis points for a 1 percentage point increase in observable risk, which we determine by estimating a quantile regression of the spread of the interest rate net of g-fees relative to the best available rates on observable risk and partialling out by the same fixed effects and controls as in column (5) of Table 1. The fact that the 10th percentile increases with observable risk suggests that markups do not fully account for the association between interest rates and observable risk. However, the shallower slope compared to the average suggests that markups also increase with observable risk.

The positive association between interest rates net of g-fees and observable risk suggests that lenders independently price for default risk, possibly due to the risk of repurchases or losing the ability to do business with the GSEs. Section 4 explains these results

[16]For ease of comparison of the slopes, Figure C.1 in Internet Appendix C.1 presents a version of Figure 2 where the average, 10th percentile, and 90th percentile are shifted so that each starts at zero for borrowers with the lowest observable risk.

[17]Consistent with the interpretation that the variation in interest rates for a given level of observable risk largely reflects markups, Figure C.2 in Internet Appendix C.1 shows that the variation is similar even when restricting to a set of mortgages that are relatively straightforward to underwrite: (no cash-out) refinance mortgages where no borrowers are self-employed, there is full income and asset documentation, the LTV ratio is no greater than 70% (which limits the probability of facing constraints due to the appraisal), and the loan amount is greater than the 25th percentile or about $146,000 (which reduces hurdles to low balance lending such as high fixed costs relative to revenue).

with a model of mortgage lender competition in which lenders bear a positive expected loss given default.

We offer several additional pieces of evidence that support the interpretation that lenders price for default risk and rule out alternative explanations.

Discount points. One potential alternative explanation is that riskier borrowers could be more likely to use discount points and lender credits to reduce upfront costs in return for a higher interest rate. However, Figure C.3 in Internet Appendix C.1 shows using the 2018 sample that total origination revenue, which is invariant with respect to the division of revenue between upfront and ongoing charges, is positively associated with observable risk. It also shows that the closing costs and secondary market components of origination revenue both generally increase with observable risk, although the latter is much stronger and appears to drive the overall association between origination revenue and observable risk. Table C.3 shows that the associations between observable risk and either closing costs or secondary marketing income are statistically significant while controlling for the full set of fixed effects and controls. They also generally hold for each of the factors that contribute to observable risk.

Interest rate fluctuations. Another interpretation is that borrowers with greater observable risk may be more likely to apply for a mortgage when interest rates are high. Our baseline specification partially controls for this by including ZIP code by year-quarter fixed effects, but it does not control for short-term fluctuations of interest rates within a quarter. To better investigate this explanation, we merge our sample from MLIS to data on interest rate locks from Optimal Blue, which has the precise lock date. Table 2 shows that the results are similar when controlling for lock rate date fixed effects.[18]

[18]Generalizing these results from the GSE segment of the market, Table C.4 in Internet Appendix C.1 shows using the Optimal Blue data that risk characteristics also appear to be priced in loans insured by government agencies, including the Federal Housing Administration (FHA), Department of Veterans Affairs (VA), and Department of Agriculture (USDA). Note that we do not include observable risk as a regressor since we estimate observable risk based on GSE loans, which are generally less risky.

Shopping. Another possibility is that observable risk could be negatively correlated with measures of financial sophistication, such as shopping and financial knowledge, which have been associated with lower interest rates (Bhutta, Fuster, and Hizmo (2021), Malliaris, Rettl, and Singh (2021)). However, Figure 2 shows that the 10th percentile of interest rates, which plausibly reflects the most aggressive shoppers for a given level of observable risk, still increases with observable risk. To further investigate this alternative explanation, we examine the association between interest rates and observable risk using data from the National Survey of Mortgage Originations (NSMO). The NSMO asks recent mortgage borrowers about their views and experiences related to obtaining their mortgage. The NSMO is conducted on a small subset of loans in the National Mortgage Database (NMDB). The NMDB is a proprietary 5% representative sample of closed-end first-lien mortgages in the U.S. maintained by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau. The NMDB is based on credit bureau data and has precise information about the borrower's interest rate and observable risk characteristics. We use an internal version of the NSMO data at the FHFA that links the NSMO responses to all the characteristics in the NMDB.

We measure shopping based on an indicator for seriously considering or applying to at least two lenders (which is positive for 54.2% of observations) and an indicator for gathering information ("A little" or "A lot") from sources other than the providing lender, including other lenders and brokers, websites, and friends, relatives, coworkers (which is positive for 77.6% of observations). Similar to Bhutta, Fuster, and Hizmo (2021), we measure financial knowledge using an index based on the borrower's self-assessed ability to explain various mortgage concepts: the process of taking out a mortgage, the difference between fixed- and adjustable- rate mortgages, the difference between interest rate and APR, amortization, and consequences of not making a required payment. We assign a score of 1, 2, or 3 for each mortgage concept depending on whether the borrower could explain it "Not at all", "Somewhat", or "Very", sum the scores for the different concepts, and then normalize the distribution to have a mean of 0 and standard deviation of 1.

Table 3 shows the results. As a benchmark, columns (1) and (2) first show that interest rates and interest rates net of g-fees increase with observable risk in the NSMO sample.[19] Columns (3) through (5) then show that this association is robust to including measures of shopping and financial knowledge. Similar to Bhutta, Fuster, and Hizmo (2021), we observe that measures of shopping and financial knowledge are associated with lower interest rates. Finally, motivated by the finding in Agarwal et al. (2020) that borrowers may be willing to accept high interest rates due to fear of rejection, column (6) includes an indicator for a borrower that applies to multiple lenders due to concern over qualifying for a loan. We find that interest rates net of g-fees are positively associated with this indicator, but they are also still positively and significantly related to observable risk. Table C.5 in Internet Appendix C.1 further shows that observable risk is negatively correlated with financial knowledge and positively associated with applying to multiple loans due to concern over qualifying for a loan.

Prepayment risk. Finally, the association between interest rates and observable risk could potentially be driven by pricing for prepayment risk.[20] However, we account for prepayments in the following ways. First, one potential determinant of prepayment speed is the loan amount, as borrowers with smaller loans may be less likely to refinance because closing costs are a larger fraction of the principal balance. We account for this channel by

[19]Note that for the NMDB sample we impute the g-fee by supposing 40 basis points for the ongoing portion and computing the risk-varying portion based on the first table of the GSEs' g-fee matrix and using a multiplier of 6 to convert the upfront charge to an annualized rate. On the MLIS sample, we find that this imputed g-fee is generally very close to the recorded g-fee.

[20]Lenders may have an incentive to charge higher interest rates for loans with a greater probability to prepay to compensate for the fact that prepayment terminates the servicing contract, reducing the value of the associated mortgage servicing rights. Additionally, from the point of view of investors of GSE mortgage-backed securities, prepayment and default have a similar impact on payouts in that both curtail total interest payments. As a result, a greater tendency to prepay could decrease the value of a loan in the secondary market if it is sold in a specified pool. Based on publicly available data from SIFMA, about 93.5% of trading volume for mortgage-backed securities (MBS) guaranteed by the GSEs during our sample period occurred in the to-be-announced market, a forward market in which the traded securities are determined after the trade. However, specified pools, in which the exact securities are determined at the time of trade, can be a more lucrative option for securities with a lower risk of prepayment when interest rates decline (Gao, Schultz, and Song (2017)).

controlling for the loan amount. Second, borrowers may use negative discount points to reduce their closing costs while taking on a higher interest rate, which tends to be associated with higher prepayment rates (Zhang (2022)). Figure C.3 and Table C.3 in Internet Appendix C.1 account for this channel by considering the total origination revenue, as discount points only shift the closing cost and secondary marketing income components of origination revenue without affecting the total. Third, we directly control for observable prepayment risk, which is defined analogously to observable risk except based on prepayment within 2 years. We also allow observable prepayment risk to depend on decile indicators for the loan amount. Table C.6 in Internet Appendix C.1 shows that observable prepayment risk has little effect on the association between interest rates and observable risk.

3.2 Interest rates and default conditional on observable risk

Figure 3 shows that interest rates net of g-fees are positively associated with default rates, even after controlling for observable risk. Similarly, column (1) of Table 4 shows that interest rates are predictive of default while also controlling for ZIP code by year-quarter fixed effects. Column (2) shows that this relationship continues to hold even after controlling for observable risk. The estimate in column (2) indicates that a 1 percentage point increase in the interest rate net of g-fees is associated with a 47 basis point increase in the default rate conditional on observable risk, which is substantial compared to the overall default rate of 50 basis points.

Column (3) shows that the association between interest rates net of g-fees and defaults is robust to controlling for a finer measure of observable risk consisting of the interaction between 10-point credit score bins (starting at 620, with an additional indicator for all credit scores below 620), 5% loan-to-value bins (starting at 60%, with an additional indicator for all loan-to-value ratios below 60%), and debt-to-income decile indicators. It is also robust to simultaneously controlling for a host of additional easily observable characteristics, including loan amount decile indicators; an indicator for full income and asset documentation; income decile indicators; family type indicators (i.e., single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; appraisal value decile indicators; an indicator for a refinance loan; an indicator for self-employed borrowers; and an indicator for first-time homebuyers.

Column (4) shows that the association between interest rates net of g-fees and defaults is weaker for relatively safe borrowers with observable risk below the median, while column (5) shows that the association is stronger for riskier borrowers with observable risk above the median. Column (6) shows that the difference between relatively safe and risky borrowers is statistically significant. Finally, column (7) shows that the result is similar when using the interest rate without subtracting out the g-fee.

These results suggest that lenders implement additional screening compared to the determinants of the upfront g-fee, especially for observably riskier borrowers. This evidence of more thorough screening for observably risky borrowers is consistent with existing findings based on mortgage lender capacity constraints that mortgages for observably riskier borrowers are relatively more time-consuming to underwrite (Sharpe and Sherlund (2016), Fuster et al. (2021)). Section 4 incorporates this result into a model of mortgage lender competition by supposing that lenders can invest in improving their underwriting practices, which allows them to observe a partially informative signal of the borrower's default risk conditional on observable risk.

As additional robustness, Figure C.4 and Table C.7 in Internet Appendix C.2 show that default is also positively associated with origination revenue in 2018.[21] Table C.8 also shows that the association between interest rates and default is robust to controlling for observable prepayment risk.

[21] Note that for loans originated in 2018 we only consider defaults within one year of origination to avoid unusual activity associated with the COVID-19 pandemic and the associated ease of forbearance.

Robustness to direct effect of interest rates on default. An alternative interpretation for the association between interest rates net of g-fees and observable risk is that higher interest rates might directly (causally) increase default risk. To estimate this direct effect, we examine variation in interest rates that is independent of pricing for default risk. We implement two approaches for doing this that are based on changes in interest rates induced by variation in the upfront g-fee. We take advantage of the fact that the direct impact of monthly payments on defaults does not depend on whether the change in interest rates comes from variation in g-fees or lender markups. Note that for these exercises we restrict to loans where the total upfront g-fee is exactly equal to the component determined by LTV and credit score.

In the first approach, we instrument interest rates using the upfront g-fee while linearly controlling for observable risk. The g-fee generally increases with the LTV ratio and decreases with the credit score, but there is still variation after controlling for observable risk, which may be due to a combination of cross-subsidization across borrowers with different risk characteristics as well as variation in observable risk associated with the DTI ratio. The exogeneity assumption is that, when controlling for observable risk, the correlation between the upfront g-fee and the default rate is only due to the former's effect on the interest rate. In particular, this means that the variation in the upfront g-fee while controlling for observable risk is not correlated with any unobservable risk. A potential concern is that borrowers that are willing to accept higher rates attributable to the upfront g-fee might be riskier. For example, borrowers near the thresholds in the upfront g-fee matrix that do not make adjustments of their LTV ratio to reduce the g-fee may be less financially sophisticated. However, this selection effect would tend to bias our estimates towards a more positive association between default rates and interest rates, which is the opposite direction as our conclusion.

Column (1) of Table 5 shows in a first-stage regression that a 100 basis point increase in up-front g-fee is associated with 16.3 basis point increase in monthly mortgage payments. Given the average PVM of 6.2, this is consistent with close to full pass-through of increase in g-fees to borrowers interest rates. As shown in Figure C.5 in Internet Appendix C.2, residual variation in the interest rate spans about 25 basis points in the interest rate. Column (2) of Table 5 then indicates a small and statistically insignificant relationship between the residual variation in the upfront g-fee and defaults. Column (3) similarly indicates a negligible relationship between interest rates, instrumented by the upfront g-fee, and defaults.

Our second approach to examine the direct effect of interest rates on default leverages discontinuities in the upfront g-fee as a function of the credit score. In particular, we focus on discontinuities where the upfront g-fee changes by at least 50 basis points (as a percentage of the loan amount). We implement a regression discontinuity approach by restricting to loans near these shifts and examining how interest rates and defaults change exactly at the shifts. A benefit of the second approach relative to the first is that it compares borrowers with more similar observable characteristics. However, a cost is that it uses a smaller sample, which could result in less precise estimates of the effect on defaults, especially since defaults are relatively rare.

As mentioned in Section 2.1, a component of the upfront g-fee varies based on a grid defined by ranges for the credit score and LTV ratio. For loans in our sample period with an LTV between 60% and 80%, the upfront g-fee matrix exhibits a discrete decline of at least 50 basis points as the credit score surpasses the credit score thresholds in the following seven cases: 660 for LTV ratios between 70.01% and 75%, 680 for LTV ratios between 60.01% and 70%, 680 for LTV ratios between 70.01% and 75%, 680 for LTV ratios between 75.01% and 80%, 700 conditional on LTV between 75.01% and 80%, 720 conditional on LTV between 70.01% and 75%, 720 conditional on LTV between 75.01% and 80%. To focus on only changes in interest rates at these thresholds and minimize the possibility that they could also affect acceptance decisions, we restrict to loans with a DTI of up to 43%. This restriction is based on the observation that 45% is the lowest DTI ratio that appears to affect acceptance decisions for GSE loans (Bosshardt et al. (Forthcoming)). On this subsample, we regress the interest rate on an indicator for having a credit score greater than or equal to the respective threshold times the change in the upfront g-fee at the threshold. We control for threshold group (i.e., an indicator for loans within a 5-point range of a given threshold) by year-month fixed effects and credit score (minus the respective threshold) times the threshold group indicators.

Figure 5a combines loans from all seven cases and shows that interest rates exhibit a discrete reduction as the credit score surpasses the respective threshold. Column (4) of Table 5 shows that a 100 basis point increase in the upfront g-fee at the thresholds is associated with a 17.5 basis point and statistically significant increase in the interest rate, which is similar to the 16.3 basis point increase in column (1). By contrast, Figure 5b indicates no discontinuous changes in default rates at the threshold. Column (5) indicates a statistically insignificant association between the upfront g-fee and defaults, albeit slightly larger in magnitude compared to the estimate in column (2). Column (6) similarly indicates an insignificant relationship between defaults and interest rates when instrumenting the latter by the change in the upfront g-fee at the thresholds. Table C.9 in Internet Appendix C additionally show how interest rates and defaults vary at the thresholds for each of the seven cases separately. Interest rates decrease in a narrow range of about 7 to 9 basis points for thresholds with a 0.5 basis point decline in the upfront g-fee, or by 17 to 18 basis points for thresholds with a 1 basis point decline in the upfront g-fee. There is greater variability in the estimated associations between the thresholds and defaults, which could be partially due to the low rate of defaults in the sample. However, all the estimates are statistically insignificant and roughly evenly split around zero.

Note that our findings of a limited effect of interest rates of delinquencies is distinct from evidence in Fuster and Willen (2017), Di Maggio et al. (2017), and Gupta (2019) that payment reductions (increases) associated with interest rate resets on adjustable-rate mortgages decrease (increase) delinquencies. In particular, our result is about the ex-ante interest rate determined at origination, whereas these papers focus on ex-post changes.[22] Note also that these papers focus on a notably riskier set of mortgages originated during the house price boom bust of the 2000s decade, with Fuster and Willen (2017) and Gupta (2019) further focusing on non-agency loans. This could be relevant since Fuster and Willen (2017) and Di Maggio et al. (2017) show that the effect of ex-post interest rate changes on defaults increases with risk characteristics such as high LTV ratios and low credit scores.

3.3 Denials and observable risk

For this observation, we use the confidential HMDA data in 2018 to examine the extent to which lenders deny applications that are accepted by the GSEs' automated underwriting systems (AUSs). Analogous to the MLIS sample, we restrict to applications for conventional, 30-year, purchase or no cash-out refinance, first lien loans for one-unit, owner-occupied, single-family non-manufactured houses. We also exclude applications for high balance loans exceeding the national baseline conforming loan limit and applications with an LTV ratio exceeding 80%. We further restrict to mortgages that are processed by exactly one AUS, which is either Desktop Underwriter (for Fannie Mae) or Loan Prospector (for Freddie Mac), and for which the result of the AUS is "Approve/Eligible" or "Accept."[23] To focus on denials that are relatively likely to reflect screening by lenders rather than problems pertaining to the application process, we exclude denials due to incomplete applications and insufficient cash at closing.[24] Note that we compute observable risk as a function of credit score, LTV, and DTI based on the model estimated with the MLIS data.[25]

[22] For example, one difference between ex-ante and ex-post variations in interest rates is that in the latter case the household income may have changed significantly from the time of mortgage origination, resulting in some households having significantly higher monthly mortgage payments relative to income.

[23] Note that about 92.6% of the sample is processed by only one AUS. The results are similar if we restrict to mortgages that receive a response of "Approve/Eligible" or "Accept" by either Desktop Underwriter (for Fannie Mae) or Loan Prospector (Freddie Mac) for at least one AUS submission.

[24] In particular, we exclude applications for which any of potentially multiple reasons for denial refers to an incomplete application or insufficient cash at closing. Note that 89% of denied applications in our sample only have one denial reason. See Table C.10 in Internet Appendix C.3 for the fraction of denials attributable to each reason.

[25] Note that we use the combined LTV (which reflects all debts secured by the property) since the HMDA data does not have the original LTV (corresponding to the individual loan application).

Figure 4 shows that denials increase with observable risk, ranging from about 1.60% for borrowers with 0.08% observable risk to 5.69% for borrowers with 1.82% observable risk. As a robustness check, Figure C.6 in Internet Appendix C.3 shows that a clear positive association remains if we remove denials due to any of the other reasons. Note that these results are similar to Bhutta, Hizmo, and Ringo (2021), who also show that lender accept/reject decisions do not fully coincide with the GSEs' AUSs. However, they focus on racial and ethnic disparities of lender and AUS denials and show how they vary across credit scores, whereas our focus is on the relationship between lender denials of AUS-accepted applications and observable risk.

3.4 Interpretation

Consistent with an intensive margin of overlays, the correlations between interest rates and both observable and unobservable risk suggest that lenders charge a risk spread on GSE mortgages that is independent of the g-fee and that predicts default. Consistent with an extensive margin of overlays, we also show that lenders deny riskier applications, even if they are accepted by the GSEs. Section 4 rationalizes these results with a model in which lenders have a positive loss given default as well as a more precise screening technology compared to what is reflected in the g-fee.

4 Model

This section develops and estimates a model of mortgage lender competition that matches the evidence from Section 3 of lenders pricing for default risk and conducting screening independently of the GSEs.

4.1 Overview

There are two types of agents: a mass of consumers denoted by i and n lenders denoted by j. There are two periods. In the first period, consumers choose whether to take out a mortgage and, if so, which lender to borrow from. To focus on the discretionary behavior of lenders as distinct from the underwriting processes of the GSEs, we specifically consider loans that satisfy the GSEs' underwriting criteria. Lenders also screen consumers and make interest rate offers. Again, to focus on the decisions of lenders as distinct from the GSEs, we assume that the interest rate is net of g-fees. The second period is a resolution in which the consumer receives the outside option payoff of zero if it did not obtain funding, otherwise, it either repays the loan or defaults.

4.2 Consumer problem

A consumer can either buy a house requiring 1 unit of external capital or take an outside option whose value is normalized to zero. If consumer i takes out a mortgage from lender j to buy a house, then the utility is given by

$$u_{ij} = \mu_i - \alpha_i r_j + \epsilon_{ij}, \tag{2}$$

where μ_i is the value of owning a house, α_i is the sensitivity to the interest rate for consumer i, r_j is the interest rate offered by lender j, and ϵ_{ij} is an unobserved idiosyncratic factor that represents the quality of the match between consumer i and lender j. For example, a higher ϵ_{ij} could represent lender j having a branch location near consumer i and therefore being more convenient. We assume that the ϵ_{ij} shocks are independently distributed and drawn from a Type I Extreme Value distribution with cumulative distribution function $F(\epsilon_{ij}) = e^{-e^{-\epsilon_{ij}}}$.

Consumers choose between the lenders and the outside option to maximize their utility. Utility maximization determines the probability of obtaining a loan from each lender as follows:[26]

$$s_j = \frac{\exp(\mu_i - \alpha_i r_j)}{1 + \sum_{j=1}^{n} \exp(\mu_i - \alpha_i r_j)}. \tag{3}$$

Note that the probability of taking the outside option is given by $1 - \sum_{j=1}^{n} s_j = \frac{1}{1+\sum_{j=1}^{n} \exp(\mu_i - \alpha_i r_j)}$.

4.3 Lender problem

Screening. There are two unobserved quality types of consumers: a mass 1 of type r consumers that repay and a mass q of type d consumers that default. Lenders screen consumers by drawing a signal z_i that indicates "low" (L), "medium" (M), or "high" (H) risk. For simplicity, we assume that a given consumer produces the same signal for all lenders.[27] The informativeness of the signal is determined by a lender's information level ψ_j. In particular, conditional on ψ_j, the distributions of the signals generated by the two types of consumers are given by

$$P(z_i|d;\psi_j) = \left\{ \begin{array}{lr} L, & \text{with probability } 0 \\ M, & \text{with probability } 1-\psi_j \\ H, & \text{with probability } \psi_j \end{array} \right\},$$

$$P(z_i|r;\psi_j) = \left\{ \begin{array}{lr} L, & \text{with probability } \psi_j \\ M, & \text{with probability } 1-\psi_j \\ H, & \text{with probability } 0 \end{array} \right\}.$$

Note that the default rate associated with each type of signal is $\delta^L = 0$, $\delta^M = \frac{q}{1+q}$, and $\delta^H = 1$.

[26] See Train (2009) for a proof.
[27] Our results are robust to an alternative model in which lenders draw different signals (see Internet Appendix F).

Each lender chooses ψ_j at a cost of

$$c(\psi_j) = \frac{k}{(1-\psi_j)^2} - k, \tag{4}$$

where k is the scale of the information cost. Note that the cost is zero when ψ_j is equal to zero, which corresponds to an uninformative signal, and the cost approaches infinity as ψ_j approaches 1, which corresponds to a perfectly informative signal. The information level represents the extent to which lenders improve their risk assessment models or invest labor hours in careful loan processing.

Profit maximization. For simplicity, we assume that a consumer's interest rate sensitivity is observable to lenders. Therefore, we can focus on the lender's problem for a set of consumers with a given interest rate sensitivity α. Suppose that a lender's cost of funding is equal to ρ. If the loan defaults, then the lender incurs an expected loss given default of $\omega \geq 0$ due to, for example, repurchase risk (Goodman (2017)). A lender's expected profits can therefore be expressed as

$$\Pi_j = \psi_j s_j^L \left(r_j^L - \rho\right) + (1-\psi_j)(1+q)s_j^M \left(r_j^M(1-\delta^M) - (\rho + \omega\delta^M)\right) - c(\psi_j), \tag{5}$$

where ψ_j is the mass of L-signal consumers, s_j^L is the probability that a L-signal consumer applies to lender j, $r_j^L - \rho$ is a lender's expected profits from lending to L-signal consumers, $(1-\psi_j)(1+q)$ is the mass of M-signal consumers, s_j^M is the probability that a M-signal consumer applies to lender j, $r_j^M(1-\delta^M) - (\rho + \omega\delta^M)$ is the lender's expected profits from lending to M-signal consumers, and $c(\psi_j)$ is the information cost. Note that lenders deny consumers with H signals since they can never yield a profit.

Each lender chooses the interest rate for each signal type r_j^z and information level ψ_j

to maximize expected profits.[28] The first order conditions for r_j^z and ψ_j yield, respectively,[29]

$$r_j^z = \frac{\rho + \omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s_j^z)}, \tag{6}$$

$$c'(\psi_j) = s_j^L\left(r_j^L - \rho\right) - (1+q)s_j^M\left(r_j^M(1-\delta^M) - (\rho + \omega\delta^M)\right). \tag{7}$$

In equation (6), the term $\frac{\rho+\omega\delta_j^z}{1-\delta_j^z}$ represents a lender's zero-profits interest rate, which we call the origination cost. The remaining term $\frac{1}{\alpha(1-s_j^z)}$ represents the markup. In equation (7), the left-hand side represents the marginal cost of increasing the information level, whereas the right-hand side corresponds to the marginal benefit derived from having a greater share of the portfolio consisting of L-signal consumers. Lending to L-signal consumers is preferable since lenders charge them lower interest rates, which causes fewer of them to substitute to the outside option.[30]

Since the solution is symmetric across lenders, we henceforth drop the j subscripts. Note that a few key properties of the model are as follows:

1. The *denial rate* is equal to the fraction of H-signal consumers: $\frac{q\psi}{1+q}$.

2. The *default rate* is equal to the fraction of defaulting consumers among consumers that receive a loan: $\frac{q(1-\psi)}{1+q(1-\psi)}$.

3. The *signal-weighted average interest rate* is a weighted average $r = \sum_z P^z r^z$, where the weights correspond to the fraction of consumers with a given signal among those that are offered a loan, i.e., $P^M = \frac{(1+q)(1-\psi)}{(1+q)(1-\psi)+\psi}$ and $P^L = \frac{\psi}{(1+q)(1-\psi)+\psi}$. Note that references to the interest rate in the model refer specifically to the signal-weighted average interest rate unless otherwise specified.

[28]Our results are qualitatively robust to an alternative model in which lenders strategically bid the interest rates (see Internet Appendix F).

[29]See Appendix A for a proof.

[30]To see this, we can substitute equation (6) into equation (7), whereby the latter becomes $c'(\psi_j) = \frac{s_j^L}{\alpha(1-s_j^L)} - \frac{s_j^M}{\alpha(1-s_j^M)}$. The right-hand side therefore has the same sign as $s_j^L - s_j^M$, which is nonnegative since L-signal consumers have lower interest rates for a given market share by equation (6) and the market shares are decreasing in the interest rate by equation (3).

4.4 Model estimation

We find the parameters to quantitatively match the observations in Section 3 using GMM, the generalized method of moments (Hansen (1982), Hansen (2022)). We focus on how the model outcomes vary with the fraction of defaulting consumers λ_d, which is also equal to $\frac{q}{1+q}$. We therefore normalize the cost of funding ρ to be zero, as it only serves to create a level shift of interest rates that can be used to capture time-varying factors that are not the focus of this exercise. We assume that the interest rate sensitivity for a given level of observable risk is uniformly distributed with probability density function $U[\alpha(\lambda_d) - \sigma, \alpha(\lambda_d) + \sigma]$, where the mean $\alpha(\lambda_d)$ linearly varies with λ_d according to $\alpha(\lambda_d) = \alpha_0 + \alpha_1 \lambda_d$. We estimate the mean value of owning a home, which we denote as μ.

The number of lenders n is directly selected to be 2, which is the median number of lenders that are seriously considered by borrowers according to the National Survey of Mortgage Originations (Bhutta, Fuster, and Hizmo (2021), Alexandrov and Koulayev (2018)).[31]

The remaining 6 parameters (μ, α_0, α_1, σ, ω, and k) are selected to match 7 moments based on the observations reported in Section 3.

Moments related to the correlation between interest rates and observable risk:

1. The variation of interest rates net of g-fees with respect to observable risk. Based on column (5) of Table 1, we find that an increase in observable risk by 1 percentage point is on average associated with a .042 percentage point increase in interest rates net of g-fees. We determine the model analog by computing the slope of the signal-weighted interest rate with respect to observable risk locally and then taking a weighted average over observable risk based on the empirical distribution.

2. The level of the interest rate net of g-fees for consumers with the lowest level of observable risk after subtracting the time-varying portion of interest rates. Based on

[31] Note that, in our sample from the National Survey of Mortgage Originations, we find that 54.2% of respondents report seriously considering or applying to at least two lenders.

Figure 2, this is equal to .23 percentage points.

3. The variation of the 10th percentile of interest rates net of g-fees with respect to observable risk. We determine this empirically by estimating a quantile regression of the spread of the interest rate net of g-fees relative to the best available rates on observable risk and partialling out by the same fixed effects and controls as in column (5) of Table 1, which is similar to the slope of the 10th percentile interest rate in Figure 2. We find that an increase in observable risk by 1 percentage point is on average associated with a .014 percentage point increase in the 10th percentile.

4. The difference between the 90th percentile and 10th percentile of interest rates net of g-fees for consumers with the lowest level of observable risk. Based on Figure 2, we find that this is equal to .49 percentage points.

Moments related to the correlation between interest rates and unobservable risk:

5 & 6. The variation of default rates with respect to interest rates while controlling for observable risk. There are two associated moments: one conditions on safe borrowers with observable risk below the median and the other conditions on risky borrowers with observable risk above the median. Based on Table 4, this correlation is equal to 11 basis points for safe borrowers and 65 basis points for risky borrowers. We determine the model analog by first computing the regression coefficient of default on the interest rate for each level of observable risk. Note that the distribution of interest rates and default rates for a given level of observable risk is determined by the variation in the interest rate sensitivity α and the signal z. We sample three values of α (the 10th percentile, 50th percentile, and 90th percentile) and, for each, weight by the endogenous frequencies of the signals. We then take a weighted average of this quotient over observable risk either below or above the median based on the empirical distribution.

Moment related to the correlation between denials and observable risk:

7. The variation in the denial rate with respect to observable risk. We determine this empirically by regressing an indicator for denial on observable risk. We find that an increase in observable risk by 1 percentage point is on average associated with a 1.92 percentage point increase in denials.

Table 6 presents the selected parameters, while Table 7 compares the empirical and model-generated values of the matched characteristics.

Table 8 shows the sensitivity of each of the moments to each of the parameters relative to the estimated parameters. For each moment there is at least one parameter such that a 10% change in the parameter induces at least a 9% change in the moment. This observation indicates that the moments respond to the parameters and supports the identification of the model. While the moments simultaneously determine all the parameters, some intuitive links are as follows. The variation of interest rates net of g-fees with respect to observable risk (moment 1) is strongly influenced by the loss given default ω, which contributes to origination costs, and the variation in the sensitivity to the interest rate α_1, which contributes to markups.[32] The level of the interest rate for consumers with the lowest level of observable risk (moment 2) relates most to the average sensitivity to the interest rate for these consumers, α_0. The variation of the 10th percentile of interest rates net of g-fees (moment 3) is strongly influenced ω.[33] The difference between the 90th percentile and 10th percentile of interest rates (moment 4) is strongly influenced by the dispersion in the sensitivity of interest rates conditional on observable risk, σ.[34] The association between interest rates and default while controlling for observable risk for safe borrowers (moment 5) is negligible near the estimated parameters. The association between interest rates and default while controlling for observable risk for risky borrowers (moment 6) is most strongly influenced by the same parameters that affect the dispersion in interest rates. The slope

[32] It is also strongly influenced by the interest rate sensitivity for low-risk borrowers α_0, since the rate of change in the markup term in equation (6) decreases with α.

[33] It is also strongly influenced by α_0 and σ since the rate of change in the markup term in equation (6) decreases with α.

[34] It is also strongly influenced by α_0 since the rate of change in the markup term in equation (6) decreases with α.

of the denial rate (moment 7) relates most to the information cost k and the consumer's value of the transaction relative to the outside option μ, which is related to the fact that the benefit of acquiring information derives from the lower tendency for L-signal consumers to substitute to the outside option.

5 Counterfactual: active vs. passive intermediation

In this section, we first show that a counterfactual in which the discretionary behavior of lenders is eliminated can in principle lead to higher or lower interest rates due to the competing effects of higher origination costs and lower markups. We then use the estimated model to determine that the counterfactual would reduce interest rates for all consumers, but to a lesser extent for observably risky consumers.

5.1 Definitions

We define *active intermediation* as the system described in the model. We define *passive intermediation* as a system in which lenders simply implement the requirements of the GSEs without any discretion. In particular, all applications that are accepted by the GSEs' underwriting criteria are offered a loan, and the interest rate for a given level of observable risk is determined by a zero-profits condition. We also assume that lenders are no longer distinguished and therefore eliminate the idiosyncratic shocks ϵ_{ij}.[35] We can summarize some key properties of passive intermediation as follows:

1. Denial rate $= 0$.

2. Default rate $= \frac{q}{1+q}$, which is also equal to λ_d.

3. Interest rate $= \frac{\rho+\omega\lambda_d}{1-\lambda_d}$, which we denote as $r_{passive}$.

[35] Note that passive intermediation yields the same result as a market with perfect competition.

To determine which system yields greater benefits for consumers, we primarily consider which generates a lower average interest rate. On the one hand, active intermediation can lead to lower origination costs since lenders screen out some of the consumers that would default. On the other hand, active intermediation also exhibits markups since lenders take advantage of distinguishing characteristics that are valued by consumers. To summarize this tradeoff, we can write the difference as

$$\begin{aligned} r_{active} - r_{passive} &= \sum_z P^z \underbrace{\left[\frac{\rho + \omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s^z)}\right]}_{r^z} - \frac{\rho + \omega\lambda_d}{1-\lambda_d} \\ &= \sum_z P^z \left[\underbrace{\frac{\rho + \omega\delta^z}{1-\delta^z} - \frac{\rho + \omega\lambda_d}{1-\lambda_d}}_{\leq 0} + \underbrace{\frac{1}{\alpha(1-s^z)}}_{>0}\right]. \end{aligned} \tag{8}$$

In the following subsection, we use the estimated model to determine which of these channels dominates.

5.2 Model results

Figure 6 compares active and passive intermediation for varying levels of λ_d, which is monotonically related to observable risk. We find that interest rates are higher for active intermediation for all levels of λ_d. Although active intermediation reduces origination costs by as much as 60% for high levels of λ_d, it is still associated with a higher interest rate due to substantial markups. The difference between the interest rates decreases with λ_d, which reflects the greater cost-saving potential of active intermediation for riskier market segments.[36] Besides the interest rate, Internet Appendix D.1 also considers the implications

[36]Note that some of the markup in active intermediation could correspond to unmodeled fixed costs, such as software, infrastructure, and facilities. To the extent that such fixed costs would also be present in passive intermediation, the interest rate in passive intermediation would also increase by a similar amount. In order for passive intermediation to generate the same interest rates as active intermediation for the riskiest borrowers, the fixed costs would have to account for about 13 basis points, or 42% of the markup for those borrowers. As borrower risk decreases, the magnitude of the fixed costs necessary to achieve the same interest rates in active and passive intermediation increases. For borrowers with the lowest risk, the fixed costs would have to account for about 20 basis points, which corresponds to almost all the markup for those borrowers.

of active and passive intermediation on the total surplus and its components.

Besides comparing active and passive intermediation, we also examine how active intermediation outcomes vary with select parameters. Figure D.2 in Internet Appendix D illustrates the role of the lender's loss given default ω. As ω increases, lenders invest more in screening and deny more applications to avoid costly defaults. They also charge higher interest rates due to the higher origination cost.

Finally, Figure D.3 in Internet Appendix D illustrates the role of competition. As the number of lenders increases, markups naturally decrease. This in turn reduces the incentive to invest in screening, resulting in a higher default rate and origination cost. Overall, stronger competition tends to reduce the differences between active and passive intermediation.[37]

5.3 Discussion on the implementation of passive intermediation

The substantial markups in active intermediation are partly driven by limited shopping, as reflected by the fact that the number of lenders seriously considered by consumers n is only equal to 2, consistent with the empirical median. This limited shopping is unlikely to be due to a lack of options, as there are about 1,700 lenders in the sample and an average of 35 lenders per county. Instead, it more likely reflects search frictions, such as having to submit detailed information to lenders to obtain and compare price quotes.

We therefore consider how these markups could potentially be reduced by more closely emulating the passive intermediation counterfactual. There are multiple possible interpretations of the counterfactual. Our baseline interpretation is that it corresponds to a market in which lenders passively implement the GSEs' underwriting and pricing requirements without being responsible for put-back risk. Theoretically, this setting produces the same result as a market in which lenders face perfect competition and have no

[37] Note, however, that active intermediation does not converge to passive intermediation as n increases, as lenders can always charge positive markups due to their product differentiation that appeals to consumers' idiosyncratic tastes.

market power. In terms of practical implementation, it can also be likened to a market in which borrowers apply for GSE loans through a standardized common mortgage application platform across lenders. Such a platform would verify the borrower's information and confirm eligibility of the application for GSE mortgages through the GSEs' automated underwriting system (AUS), then disseminate the information of AUS approved borrowers to lenders. Lenders could then make binding offers based on the information provided on the platform. Such a platform could ensure that lenders have access to the same information as well as allow borrowers to easily apply to and compare offers from many lenders. Note that an important requirement for this platform to work is to remove the put-back risk.

6 Extension: heterogeneous lenders

In this section, we extend our analysis to examine how intermediation patterns vary by lender type, specifically focusing on banks versus nonbanks. We observe that nonbanks are associated with greater observable risk, greater interest rates conditional on observable risk, and greater default rates conditional on observable risk. We then rationalize these observations with a model in which nonbank lenders have a lower expected loss given default and a higher funding cost.

6.1 Empirical variation in intermediation patterns by lender type

Figure 7 compares banks and nonbanks with respect to three characteristics as a function of observable risk.

First, Figure 7a shows that the market share of nonbanks increases with observable risk. Column (2) of Table 9 shows that the likelihood of a nonbank lender increases by about 3.8 percentage points for a 1 percentage point increase in observable risk when including ZIP code by year-quarter fixed effects and controlling for loan amount decile indicators and an indicator for full income and asset documentation. This result is similar to the findings in Buchak et al. (2018) and Kim et al. (2018) that nonbanks are associated with lower credit scores and higher debt-to-income ratios for GSE loans. However, our result is distinct from the conclusion in Buchak et al. (2018) that nonbank borrowers are not clearly more or less creditworthy due to also being associated with lower loan-to-value ratios. We also observe that nonbanks are associated with lower loan-to-value ratios (see Table E.1 in Internet Appendix E), but we nevertheless find that they are associated with an average 11 basis points higher default risk (relative to a mean of 50 basis points) based on our measure of observable risk that jointly incorporates credit scores, higher debt-to-income ratios, and loan-to-value ratios.[38]

Second, Figure 7b shows that nonbanks are associated with higher interest rates net of g-fees conditional on observable risk. Column (2) of Table 9 shows that the average difference is about 4.8 basis points, while column (3) shows that the difference slightly increases with observable risk.[39] This observation, which is similar to other results in the literature (e.g., Buchak et al. (2018), Benson, Kim, and Pence (2023)), is consistent with nonbanks having higher funding costs, possibly due to nonbanks' use of warehouse financing lines rather than insured deposits (e.g., Jiang (2023)). It is also consistent with nonbanks exhibiting higher default rates conditional on observable risk, as described further in the next paragraph.

Third, Figure 7c shows that nonbanks are associated with higher default rates conditional on observable risk. Column (4) of Table 9 shows that the average difference between banks and nonbanks is 16.8 basis points, which is substantial relative to the average default rate of 50 basis points. Column (5) shows that the difference is only 2.6 basis points and sta-

[38]To supplement the market shares in Figure 7a, Figure E.1 in Internet Appendix E shows that the kernel density and cumulative distribution function of observable risk are slightly more concentrated at higher values for nonbanks compared to banks. Additionally, the histograms in Figure E.2 show that nonbanks are associated with lower credit scores, higher debt-to-income ratios, lower loan-to-value ratios, and higher observable risk.

[39]Table E.2 in Internet Appendix E shows that the results are similar when using origination revenue rather than the interest rate. Table E.3 shows that the results are similar when comparing banks to either nonbank-fintechs or nonbank-nonfintechs. Nonbank-fintechs are associated with generally higher interest rates, which could also reflect a premium for greater convenience (Buchak et al. (2018)). Possibly relatedly, columns (4) through (6) of Table E.7 in Internet Appendix E show using a merge of the MLIS data with the NSMO survey that fintechs are associated with higher measures of borrower satisfaction.

tistically insignificant for low-risk borrowers, but it increases by 27.8 basis points for each percentage point of observable risk.[40,41] This observation updates previous work indicating that the association between nonbanks and default for GSE loans is small in magnitude (Buchak et al. (2018)) or insignificant (Kim et al. (2022)). In particular, we focus on a sample of loans originated in 2016-2017, whereas Buchak et al. (2018) focuses on loans originated in 2010-2013 and Kim et al. (2022) considers loans originated in 2005-2015. Figure E.3c and Table E.6 in Internet Appendix E show that the association between nonbanks and defaults became more positive from 2013 to 2017.[42]

6.2 Model with heterogeneous lenders

In this section, we use extensions of the model with heterogeneous lenders to determine that the differences between banks and nonbanks are more consistent with the latter having a lower expected loss given default rather than differences in screening costs. We also consider the implications of this result for the increasing market share of nonbanks.

Figure 8 shows various model outcomes as a function of λ_d when there is heterogeneity in the loss given default ω, screening cost k, or funding cost ρ.

In the case of heterogeneous loss given default, the low loss given default lender originates relatively more loans as λ_d increases. This higher weighting on observably risky borrowers is driven by two factors. First, the low loss given default lender acquires less information, which results in a lower denial rate. Second, it also charges a lower interest rate

[40] Table E.3 in Internet Appendix E shows that the results are similar when comparing banks to nonbank-nonfintechs. Nonbank-fintechs tend to have more defaults for low levels of observable risk but less steep of an increase with observable risk.

[41] Consistent with nonbanks lending more to borrowers with higher unobservable risk, columns (1) through (3) of Table E.7 in Internet Appendix E show using a merge of the MLIS data with the NSMO survey that nonbanks are associated with higher measures of a borrower's self-assessed risk while controlling for observable risk. Self-assessed risk is computed in a manner analogous to the financial knowledge index described in Section 3.1 except based on the survey questions asking about the borrower's concern about qualifying for a loan; expectations of being unable to meet payments, experiencing a layoff, or other personal financial crisis; and, contingent on a financial crisis occurring, the perceived ability to continue making payments, receive help from family or friends, obtain a loan, or increase income.

[42] Note that Figure E.3b and Table E.4 show that the association between nonbanks and observable risk slightly increased during this period. Figure E.3c and Table E.5 show that the association between nonbanks and interest rates also slightly increased.

conditional on a borrower's signal, which allows it to attract more borrowers. This pricing advantage becomes more pronounced for borrowers with greater observable risk since the lower rate of loss given default has a larger absolute impact. Note that the low loss given default lender still has about the same or slightly higher interest rates on average since a greater fraction of its borrowers have weaker signals. Overall, these patterns are consistent with the empirical risk profile of nonbanks relative to banks, as Figure 7a shows that nonbanks lend more to observably risky consumers, Figure 7b shows that nonbanks have higher interest rates conditional on observable risk, and Figure 7c shows that nonbanks experience more defaults conditional on observable risk.

In the case of heterogeneous screening costs, similar to the low loss given default lender in the previous case, the high screening cost lender acquires less information, resulting in a lower denial rate and higher default rate. It also has a higher average interest rate to compensate for this risk, which is driven by the fact that a greater fraction of its borrowers have weaker signals. However, conditional on a borrower's signal, the high screening cost lender charges the same interest rate as the low screening cost lender. Therefore, the high screening cost lender lacks an analogous pricing advantage to the low loss given default lender. As a result, even if we select the differences in screening costs to generate approximately the same difference in the default rate as the case with heterogeneous loss given default, we observe a smaller and opposite overall effect on observable risk, in contrast to Figure 7a.

Finally, in the case of heterogeneous funding costs, the lender with higher funding costs naturally charges higher interest rates, resulting in a lower market share. These differences are mostly constant with respect to observable risk. The difference in the default rate is small by comparison.

Overall, the empirical findings are more consistent with nonbanks having a lower expected loss given default rather than screening costs. This lower expected loss given default could be attributable to nonbanks typically being monolines and therefore having less of a concern to protect profits from other product offerings. The higher interest rates charged by nonbanks even for low risk borrowers is consistent with nonbanks also having higher funding costs. Figure 9 shows that associating nonbanks with a higher funding cost and lower loss given default qualitatively emulates the empirical observations in Figure 7.[43] Based on the association between nonbanks and lower funding costs, Figure D.2 suggests that a transition from a market dominated by banks to a market dominated by nonbanks would result in higher default rates. It would also result in relatively lower interest rates for risky borrowers, although the absolute effect on interest rates would also depend on the relative magnitudes of the difference in the loss given default and funding costs.

Figure E.4 in Internet Appendix E further shows that the observed increasing market share and default rates of nonbanks from 2013 to 2017 is consistent with three changes in the model. The first change is a consumer preference shock in favor of nonbanks, which we model by adding a term $A * 1_{\{nonbank\}}$ in the utility (2). This preference shock increases the nonbank market share and interest rate. The second change is a relative reduction in nonbanks' cost of funding ρ, which also increases nonbanks' market share but decreases their interest rates relative to banks. The consumer preference shock and cost of funding shock are jointly determined to significantly increase nonbanks' market share while only slightly increasing their interest rates. Finally, the third change is a relative reduction in nonbanks' loss given default ω, which increases their default rates and leads to a slightly stronger correlation between nonbanks and observable risk.

7 Conclusion

We provide evidence of active intermediation by lenders of GSE mortgages. Specifically, we show that mortgage interest rates net of g-fees increase with observable risk, consistent with discretionary pricing for risk. Interest rates also predict default conditional on

[43]The model generates less steep of an increase in the market share compared to Figure 7a. However, a comparison of column (1) and column (2) of Table 9 suggests that the empirical slope with observable risk becomes less steep after accounting for geographic fixed effects and other controls.

observable risk, consistent with lender screening. We develop a model of mortgage lender competition with screening that explains these observations by supposing that lenders of GSE mortgages face a positive expected loss given default. The model shows that lender discretion reduces costs but also results in substantial markups, resulting in higher interest rates, although to a lesser extent for observably risky borrowers.

In an extension of our analysis focused on different types of lenders, we observe that nonbanks, which comprise an increasing share of the mortgage market, exhibit different intermediation patterns compared to banks, such as higher observable risk, higher default rates conditional on observable risk, and higher interest rates conditional on observable risk. The model suggests that these differences are consistent with nonbanks having a lower expected loss given default. The model suggests that the increasing market share of nonbanks may lead to an increase in default rates and less steep of an increase in interest rates with respect to observable risk.

From a policy perspective, our counterfactual analysis suggests that implementing the GSE segment of the mortgage through private intermediaries is most likely to benefit observably risky borrowers, if any. Additionally, while the increasing presence of nonbank lenders, which are more associated with observably risky consumers, could improve access to credit, it could also lead to a riskier pool of consumers, albeit still within the underwriting requirements of the GSEs.

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8 Figures

Figure 1: Interest rates and observable risk

This figure presents a binned scatterplot of the interest rate and the interest rate net of the total g-fee on observable risk while controlling for origination year-month fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

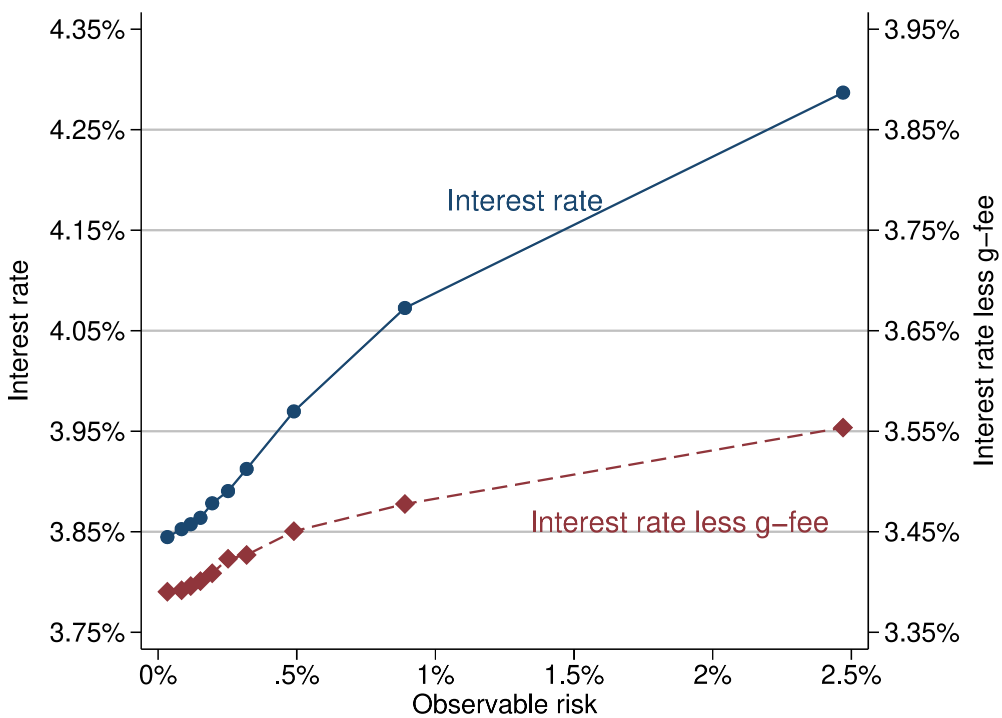


Figure 2: Interest rates and observable risk: average and dispersion

This figure shows the 10th percentile, 90th percentile, and average of the spread of the interest rate net of the total g-fee relative to the best available rate for deciles of observable risk. The best available rate is determined by computing the 10th percentile of the interest rate net of the total g-fee for the borrowers in the lowest quartile of observable risk in each week (i.e., observable risk less than 12.5 basis points for the average week). Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

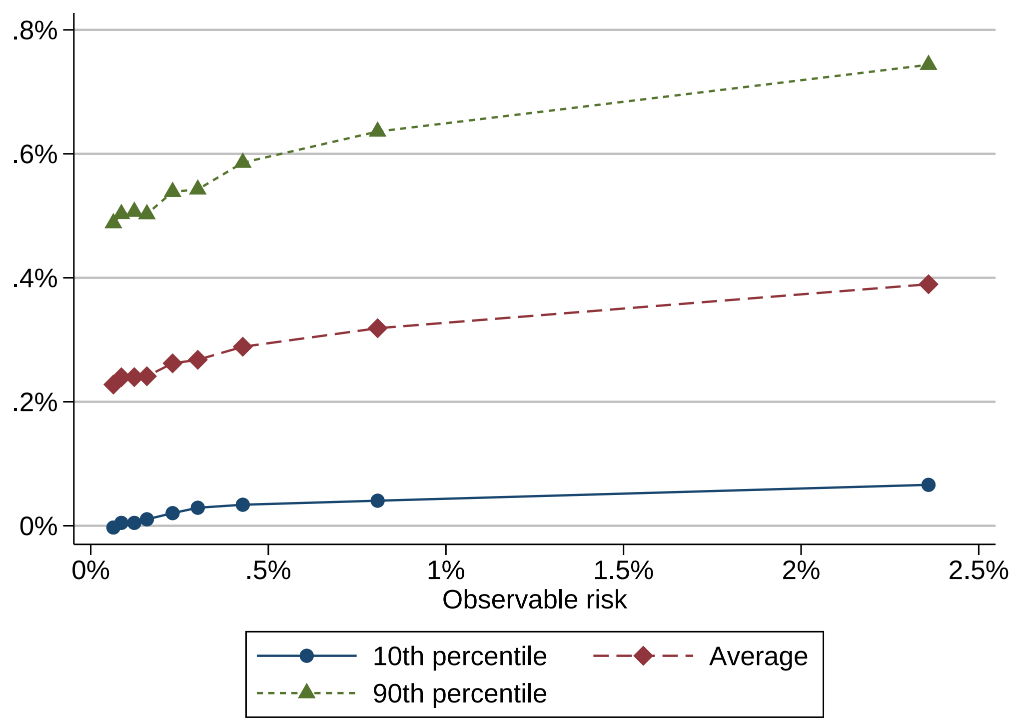


Figure 3: Interest rates and default

This figure presents a binned scatterplot of default (multiplied by 100) on the interest rate net of the total g-fee while controlling for origination year-month fixed effects and observable risk, as well as a version that does not control for observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

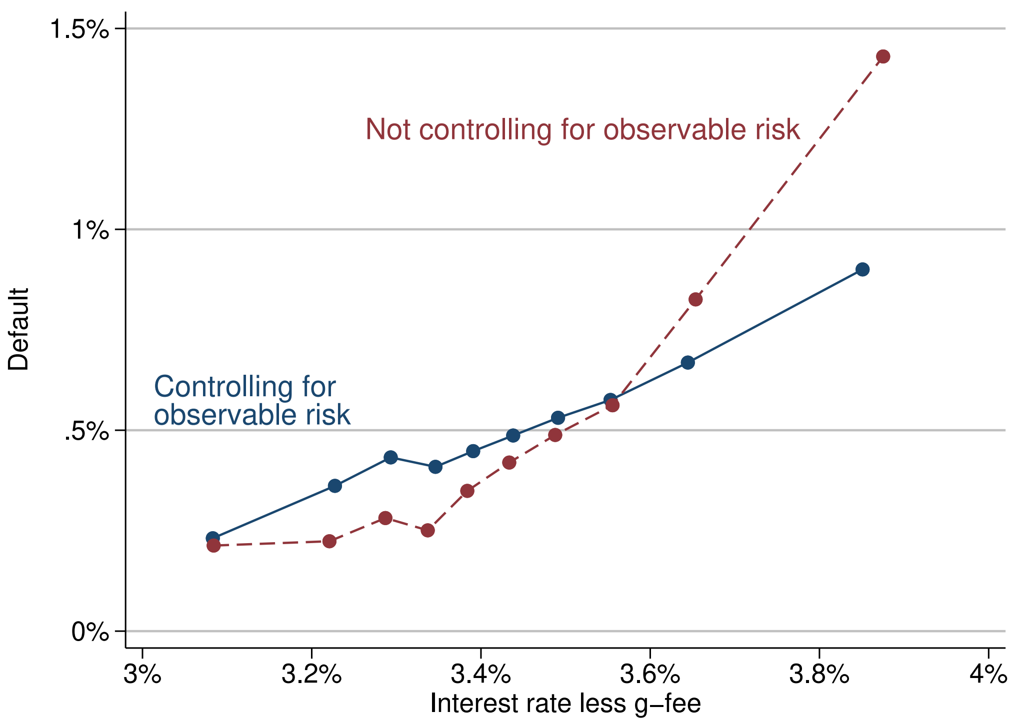


Figure 4: Application denials and observable risk

This figure presents a binned scatterplot of the denial rate for mortgages accepted by the GSEs' automated underwriting systems on observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. which is estimated using the MLIS data. Source: confidential HMDA, 2018, restricting to approved or denied applications accepted by the GSE automated underwriting systems for conventional, 30-year, purchase or no cash-out refinance, first lien loan applications for one-unit, owner-occupied, single-family non-manufactured houses and excluding high balance loans exceeding the base conforming loan limit and loans with a combined loan-to-value ratio exceeding 80%. We also exclude denials due to incomplete applications and insufficient cash at closing.

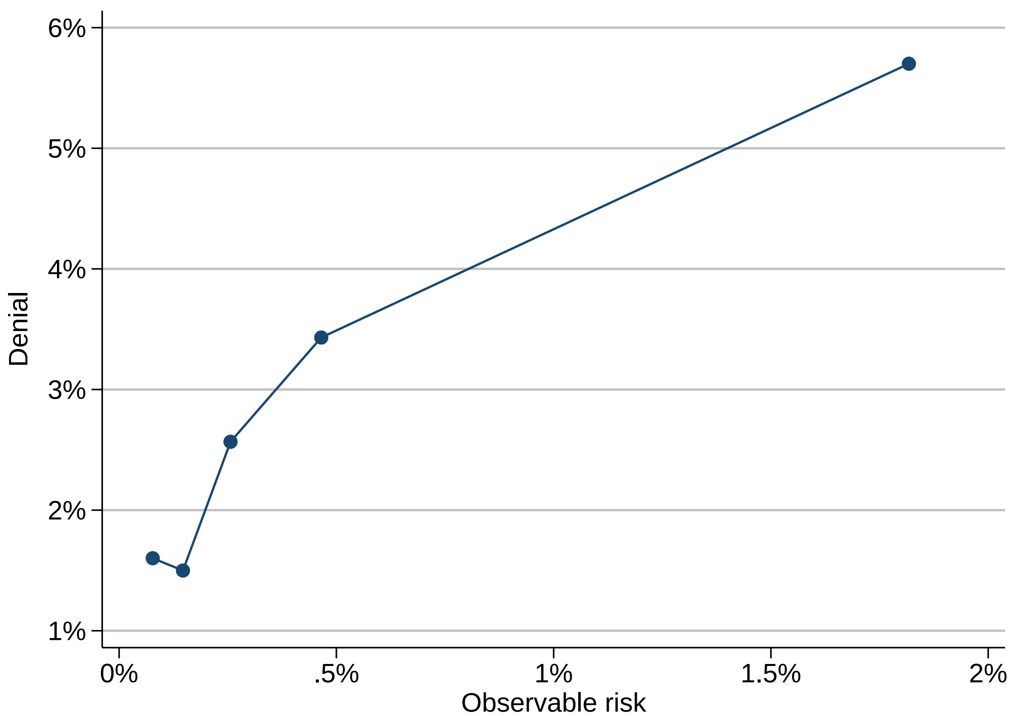
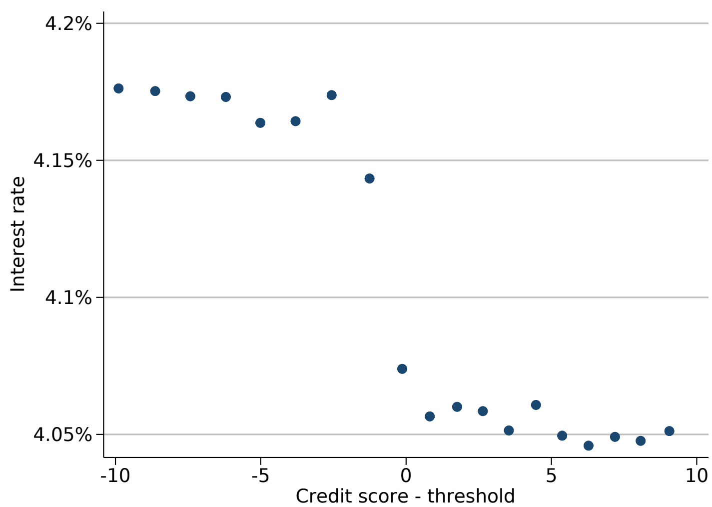


Figure 5: Interest rates and defaults at each g-fee threshold

These figures restrict to loans with a loan-to-value (LTV) ratio and credit score such that the credit score is within 10 points of a threshold where the upfront g-fee changes by at least 50 basis points. Figure 5a shows a binned scatterplot of the interest rate on credit score (minus the respective threshold) while controlling for threshold by year-month fixed effects. Figure 5b is similar except that the y-axis corresponds to the default rate. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, loans with debt-to-income ratio up to 43%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix.

(a) Interest rates



(b) Defaults

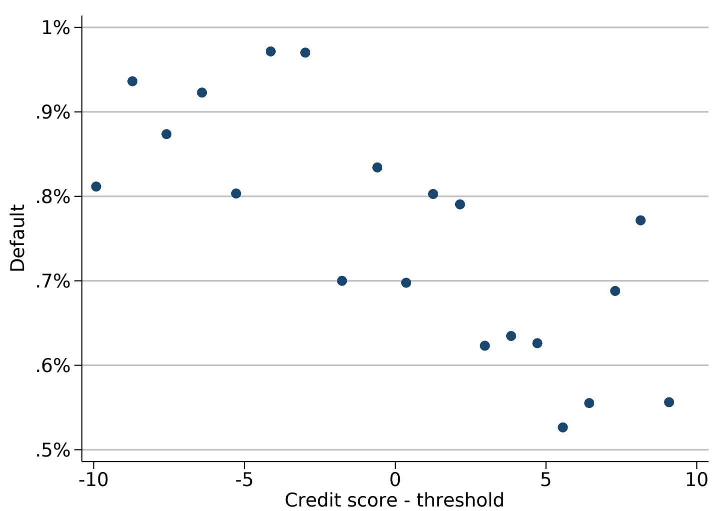


Figure 6: Active and passive intermediation

These figures show various features of the model of active intermediation (the baseline model in which lenders screen the applicant, approve or deny the application, and engage in imperfect competition to determine the interest rate) and passive intermediation (a setting where all applications approved by the GSEs are originated and the interest rate is determined by a zero-profits condition) for various levels of λ_d. The *denial rate* is the probability that a consumer's loan application is rejected. The *default rate* is the fraction of approved applications that consist of defaulting consumers. The *interest rate (IR)* for active intermediation is decomposed as the *origination cost* (which is the zero-profits interest rate), the *information cost* (which is the cost associated with the information level ψ), and *markups less information cost*. See Table 6 for parameters.

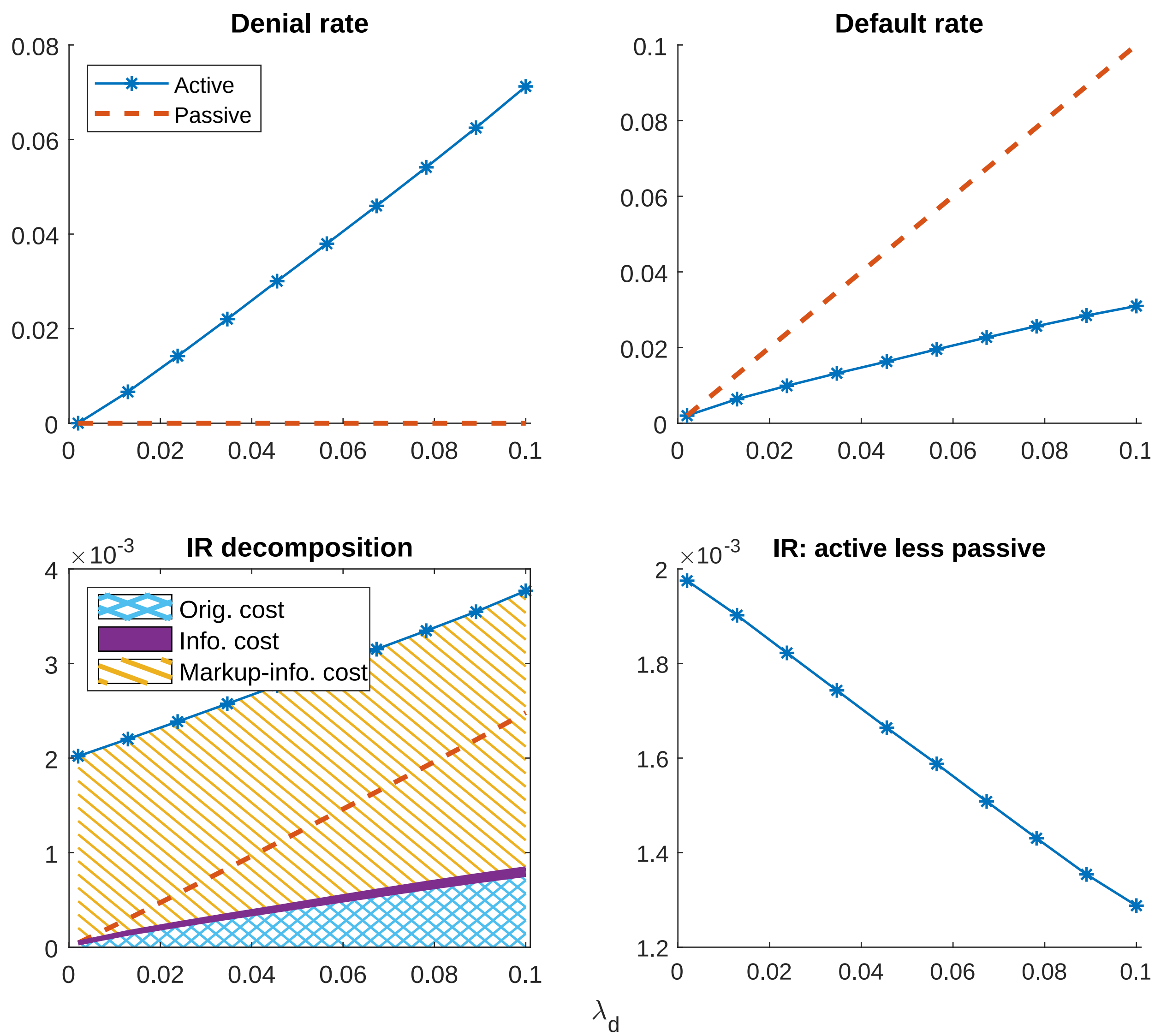
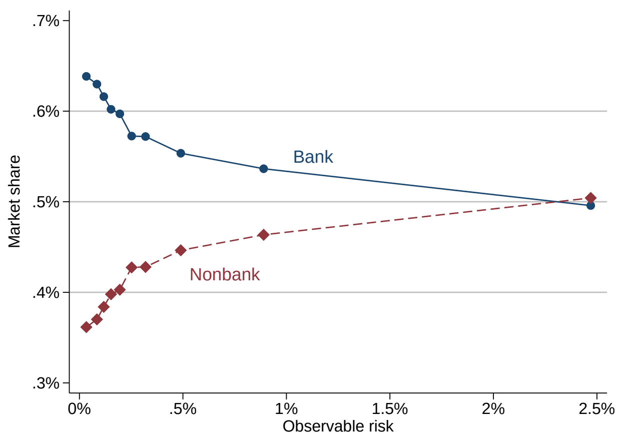


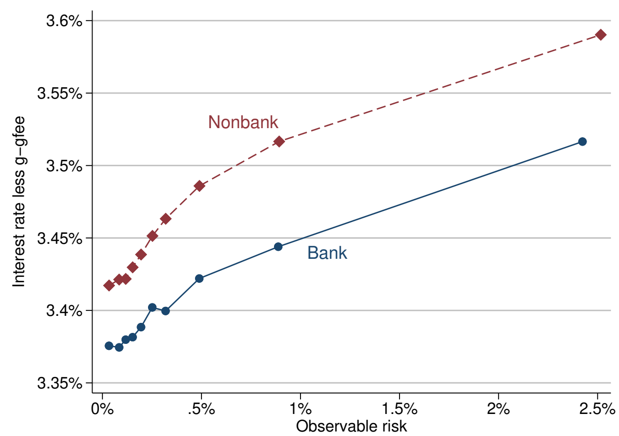
Figure 7: Empirical comparison of banks and nonbanks

Figure 7a presents a binned scatterplot of dummy variables indicating whether a loan was sold to the GSEs by a bank or a nonbank on observable risk while controlling for origination year-month fixed effects. These estimates correspond to the respective market shares. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Figure 7b presents a binned scatterplot of the interest rate net of the total g-fee on observable risk while controlling for origination year-month fixed effects and splitting by bank and nonbank sellers. Figure 7c presents a binned scatterplot of default (multiplied by 100) on the interest rate net of the total g-fee while controlling for origination year-month fixed effects and observable risk and splitting by bank and nonbank sellers. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

(a) Market share and observable risk



(b) Interest rates and observable risk



(c) Default and observable risk

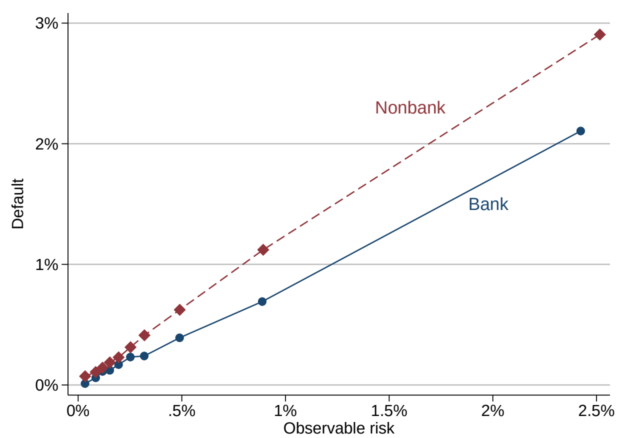


Figure 8: Comparison of heterogeneous ω, k, and ρ

These figures show various features of the version of the model with 2 lenders and heterogenous loss given default ω (left panels), heterogeneous cost of screening k (middle panels), or heterogeneous funding costs (right panels). The *origination market share* refers to the share of originated loans associated with a particular lender. The *interest rate* (IR) is the signal-weighted average interest rate, as described further in Section 4.3. The *default rate* is the fraction of approved applications that consist of defaulting consumers.

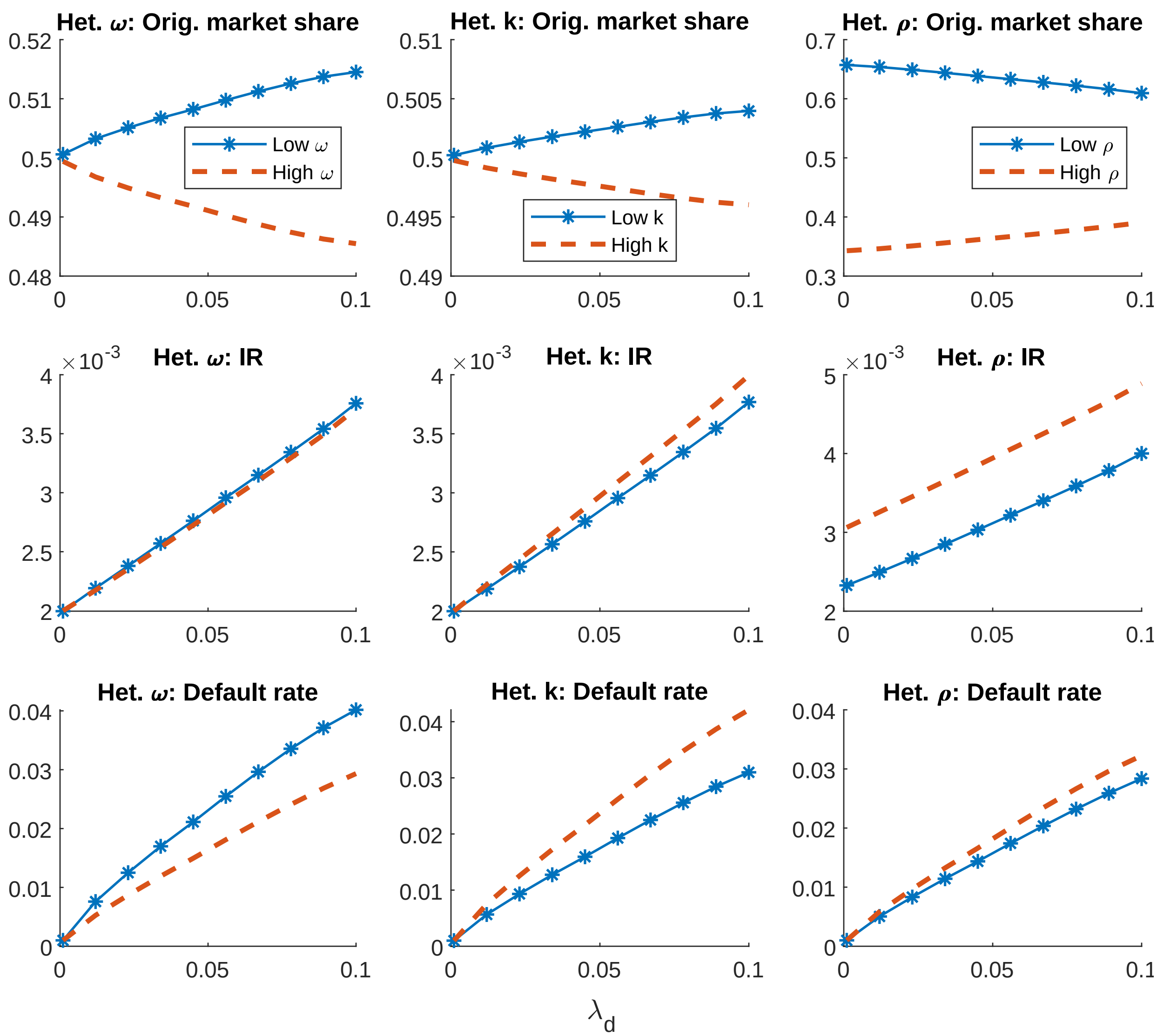
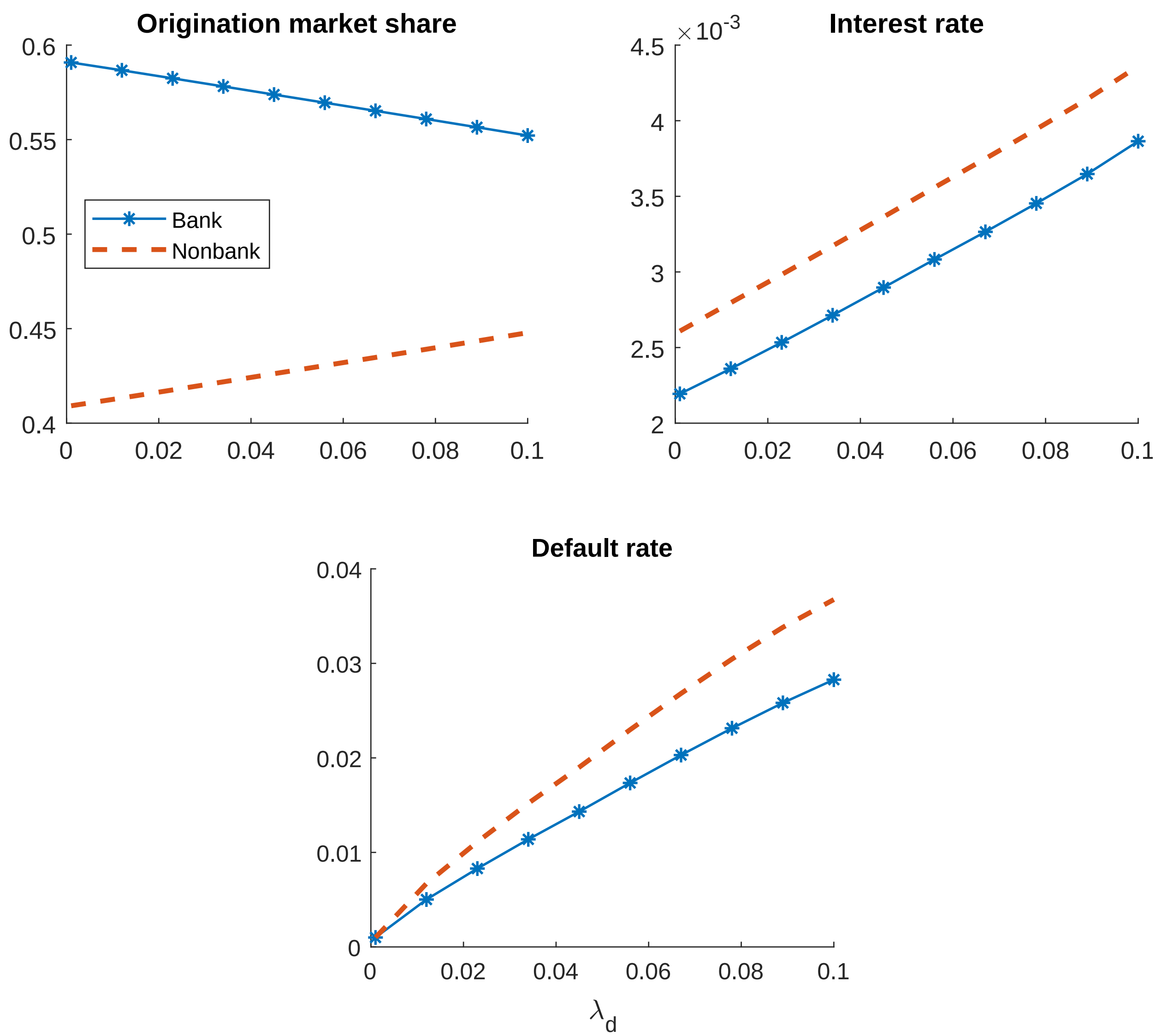


Figure 9: Model emulation of banks and nonbanks

These figures show various features of the version of the model with a bank lender and a nonbank lender. The nonbank lender has higher funding costs ρ and lower loss given default ω. The *origination market share* refers to the share of originated loans associated with a particular lender. The *interest rate* (IR) is the signal-weighted average interest rate, as described further in Section 4.3. The *default rate* is the fraction of approved applications that consist of defaulting consumers.



9 Tables

Table 1: Interest rates and observable risk

	(1) IR	(2) IR	(3) IR	(4) IR-gfee	(5) IR-gfee	(6) IR-gfee
Observable risk	0.152***	0.149***		0.047***	0.042***	
	(349.96)	(340.94)		(130.55)	(123.41)	
Credit score			-0.216***			-0.063***
			(-353.79)			(-120.08)
LTV			0.324***			-0.020***
			(141.79)			(-9.55)
DTI			0.107***			0.120***
			(41.12)			(50.20)
Observations	875,464	875,464	875,464	875,464	875,464	875,464
R^2	0.674	0.681	0.680	0.670	0.696	0.697
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes

Note: Column (1) regresses the interest rate on observable risk while controlling for ZIP code by year-quarter fixed effects and seller by year-quarter fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Column (2) adds the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Column (3) regresses the interest rate on the credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio (each divided by 100). Columns (4), (5), and (6) are analogous except that the dependent variable is the interest rate net of the total g-fee. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table 2: Interest rates and observable risk with lock date fixed effects

	(1) IR	(2) IR-gfee	(3) IR-gfee	(4) IR-gfee
Observable risk	0.144***	0.043***	0.041***	
	(137.28)	(50.68)	(53.94)	
Credit score				-0.060***
				(-51.35)
LTV				-0.016***
				(-3.55)
DTI				0.101***
				(19.54)
Observations	132,871	132,762	132,745	132,745
R^2	0.736	0.759	0.825	0.825
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes
Seller $\times$ Year-quarter FE	Yes	Yes	Yes	Yes
Lock date FE	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Column (1) regresses the interest rate on observable risk while controlling for ZIP code by year-quarter fixed effects, seller by year-quarter fixed effects, and the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1 (based on the model estimated using the MLIS sample). Column (2) is similar except that the dependent variable is the interest rate net of the total g-fee. Column (3) includes lock date fixed effects. Column (4) is similar to column (3) except regressing the interest rate on the credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio (each divided by 100). T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: MLIS merged with Optimal Blue rate lock data, 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family houses and excluding high balance loans exceeding the base conforming loan limit, loans with a loan-to-value ratio exceeding 80%, and loans with subordinate financing.

Table 3: Interest rates and observable risk controlling for shopping and financial knowledge

	(1) IR	(2) IR-gfee	(3) IR-gfee	(4) IR-gfee	(5) IR-gfee	(6) IR-gfee
Observable risk	0.233***	0.040***	0.039***	0.039***	0.036**	0.030**
	(14.76)	(2.74)	(2.74)	(2.73)	(2.48)	(2.05)
Considered or applied to at least 2 lenders			-0.032***	-0.025**	-0.021**	-0.029***
			(-3.28)	(-2.51)	(-2.09)	(-2.81)
Gathered information				-0.024**	-0.026**	-0.026**
				(-2.04)	(-2.18)	(-2.25)
Index of mortgage knowledge					-0.018***	-0.017***
					(-3.59)	(-3.45)
Applied to >1 because concerned						0.084***
						(3.44)
Observations	4,408	4,408	4,408	4,408	4,408	4,408
R^2	0.626	0.609	0.610	0.611	0.612	0.614
State $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Column (1) regresses the interest rate on observable risk while controlling for state by year-quarter fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1 (computing observable risk within the NMDB sample). Column (2) is similar to column (1) except subtracting an imputed g-fee as a function of credit score and LTV based on the first table of the GSEs' g-fee matrix. Column (3) adds an indicator for seriously considering or applying to at least 2 lenders. Column (4) adds an indicator for obtaining information from other lenders, the internet, or friends, relatives, or coworkers. Column (5) adds an index of mortgage knowledge as described in Section 3.1, normalized to have a standard deviation of 1. Column (6) adds an indicator for a borrower that applies to more than one lender due to concern over qualifying for a loan. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: National Survey of Mortgage Originations, 2013-2017, restricting to GSE-acquired, fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, site-built properties and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%.

Table 4: Interest rates and default

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Default	Default	Default	Default	Default	Default	Default
IR - g-fee	1.057***	0.471***	0.419***	0.112***	0.650***	0.112***	
	(21.76)	(10.11)	(8.61)	(3.49)	(7.69)	(3.48)	
Observable risk		0.924***		0.786***	0.928***	0.786***	0.890***
		(40.44)		(5.87)	(33.13)	(5.87)	(36.53)
IR - g-fee × Risky						0.538***	
						(5.95)	
Observable risk × Risky						0.142	
						(1.04)	
IR							0.370***
							(7.99)
Observations	875,464	875,464	875,464	409,879	426,296	836,175	875,464
R^2	0.155	0.163	0.166	0.230	0.223	0.226	0.163
ZIP × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	No	Yes
ZIP × Year-quarter × Risky FE	No	No	No	No	No	Yes	No
Seller × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	No	Yes
Seller × Year-quarter × Risky FE	No	No	No	No	No	Yes	No
Controls	No	No	Yes	No	No	No	No
Sample	Full	Full	Full	Safe	Risky	Full	Full

Note: Column (1) regresses an indicator for default (multiplied by 100) on the interest rate net of the total g-fee while controlling for ZIP code by year-quarter fixed effects and seller by year-quarter fixed effects. Column (2) adds observable risk as a regressor. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Column (3) instead includes the following controls: the interaction between 10-point credit score bins (starting at 620, with an additional indicator for all credit scores below 620), 5% loan-to-value bins (starting at 60%, with an additional indicator for all loan-to-value ratios below 60%), and debt-to-income decile indicators (note that this interaction absorbs observable risk); loan amount decile indicators; an indicator for full income and asset documentation; income decile indicators; family type indicators (i.e., single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; appraisal value decile indicators; an indicator for a refinance loan; an indicator for self-employed borrowers; and an indicator for first-time homebuyers. Column (4) estimates the specification in column (2) except restricting to relatively safe borrowers with observable risk below the median. Column (5) estimates the specification in column (2) except restricting to relatively risky borrowers with observable risk above the median. Column (6) estimates the specification in column (2) except interacting all the regressors with a dummy variable *Risky* indicating borrowers with observable risk above the median. Column (7) estimates the specification in column (2) except using the interest rate (without subtracting out the g-fee) as the dependent variable. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table 5: G-fee induced variation in interest rates and default

	(1) IR (First stage)	(2) Default (Red. form)	(3) Default (IV)	(4) IR (First stage)	(5) Default (Red. form)	(6) Default (IV)
Upfront g-fee	0.163***	-0.004				
	(271.04)	(-0.13)				
Observable risk	0.044***	0.940***	0.941***			
	(80.21)	(27.35)	(22.95)			
Interest rate			-0.026			-0.864
			(-0.13)			(-0.52)
Above threshold $\times \Delta$ upfront g-fee				0.175***	-0.151	
				(22.91)	(-0.52)	
Observations	809,443	809,443	809,443	38,292	38,292	38,292
R^2	0.723	0.171	0.010	0.532	0.007	-0.002
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	No	No	No
Seller $\times$ Year-quarter FE	Yes	Yes	Yes	No	No	No
Controls	Yes	Yes	Yes	No	No	No
Threshold $\times$ Year-month FE	No	No	No	Yes	Yes	Yes
Threshold dummy $\times$ Credit score	No	No	No	Yes	Yes	Yes

Note: Column (1) regresses the interest rate on the upfront g-fee and observable risk while controlling for ZIP code by year-quarter fixed effects, seller by year-quarter fixed effects, and the following controls: loan amount decile indicators and an indicator for full asset and income documentation. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Column (2) regresses an indicator for default (multiplied by 100) on the upfront g-fee and observable risk. Column (3) regresses an indicator for default (multiplied by 100) on the interest rate and observable risk, instrumenting the interest rate by the upfront g-fee. Columns (4) through (6) restrict to loans with a loan-to-value (LTV) ratio and credit score such that the credit score is within 5 points of a threshold where the upfront g-fee changes by at least 50 basis points. Column (4) regresses the interest rate on an indicator for having a credit score greater than or equal to the respective threshold times the change in the upfront g-fee at the threshold, and it controls for threshold group (i.e., an indicator for loans within a 5-point range of a given threshold) by year-month fixed effects and credit score (minus the respective threshold) times the threshold group indicators. Column (5) is similar to column (4) except that the dependent variable is an indicator for default (multiplied by 100). Column (6) is similar to column (5) except that we regress the default indicator on interest rates, which we instrument by the change in the upfront g-fee at the respective threshold. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix. Columns (4) through (6) additional restrict to loans with a DTI up to 43%.

Table 6: Estimated parameters

Parameter	Value	Standard error
Borrower utility of borrowing (μ)	2.882	(.0357)
Level of sensitivity to interest rate (α_0)	8.918	(.137)
Variation in sensitivity to interest rate (α_1)	–33.318	(.370)
Sensitivity to interest rate dispersion (σ)	7.130	(.111)
Lender loss given default (ω)	2.232	(.120)
Information cost scale (k)	5.460e-04	(7.697e-05)

Note: Parameters related to the interest rate sensitivity (α_0, α_1, and σ) are scaled such that the interest rate sensitivity corresponds to the decrease in utility associated with a 1 percentage point increase in the interest rate. The lender loss given default ω is scaled as a percentage of the loaned amount. The information cost scale k is scaled in a manner consistent with lender profits in equation (5) being expressed as a percentage of the loaned amount.

Table 7: Empirical and model generated moments

Variable	Empirical	Model
Slope of interest rate wrt. obs. risk	0.0419	0.0388
Interest rate for borrowers with low obs. risk	0.0023	0.0020
Slope of 10th pctile. interest rate wrt. obs. risk	0.0140	0.0259
Difference between 90th pctile. and 10th pctile. for low obs. risk	0.0049	0.0044
Slope of default wrt. interest rate (safe)	0.1120	0
Slope of default wrt. interest rate (risky)	0.6499	0.3617
Slope of denial rate to obs. risk	1.9199	1.2561

Note: All rates are expressed as fractions. For example, 1 percentage point is expressed as .01. “Interest rate” in the variable description refers to interest rate net of g-fees.

Table 8: Sensitivity analysis

(a) Levels

	Base	μ	α_0	α_1	σ	ω	k
IR slope: avg	.0388	.0386	.0351	.0408	.0388	.0433	.0357
IR level: avg	.002	.0021	.0018	.002	.002	.002	.002
IR slope: p10	.0259	.026	.0143	.0265	.0188	.0293	.0249
IR level: p90-p10	.0044	.0045	.0031	.0044	.0048	.0044	.0044
Corr. IR and default (safe)	0	0	0	0	.0003	0	0
Corr. IR and default (risky)	.3618	.4248	.858	.3212	.2681	.3969	.3594
Denial: slope	1.2561	1.131	1.2628	1.2548	1.2561	1.4166	.9048

(b) Relative changes

	μ	α_0	α_1	σ	ω	k
IR slope: avg	-.0041	-.0953	.0511	0	.1173	-.0788
IR level: avg	.024	-.0899	.0006	0	.0031	-.0006
IR slope: p10	.0065	-.4472	.0241	-.2739	.1332	-.0374
IR level: p90-p10	.0242	-.2859	.0021	.0971	0	0
Corr. IR and default (risky)	.1744	1.3718	-.1121	-.259	.097	-.0066
Denial: slope	-.0996	.0053	-.001	0	.1278	-.2796

Note: Table 8a shows the values of the observables at the estimated parameters in the "Base" column, and for the columns labeled by a parameter it shows the values of the moments when that parameter increases by 10% while the remaining parameters are kept at the estimated level. Table 8b shows the corresponding change in the observable relative to its level at the estimated parameters.

Table 9: Empirical comparison of banks and nonbanks

	(1) Nonbank	(2) Nonbank	(3) IR-gfee	(4) IR-gfee	(5) Default	(6) Default
Observable risk	4.718***	3.825***	0.048***	0.045***	0.947***	0.806***
	(68.33)	(52.39)	(132.83)	(91.92)	(41.78)	(27.53)
Nonbank			0.048***	0.046***	0.168***	0.026
			(95.32)	(77.48)	(9.87)	(1.32)
Observable risk $\times$ Nonbank				0.004***		0.278***
				(6.21)		(6.18)
Observations	875,464	875,464	875,464	875,464	875,464	875,464
R^2	0.007	0.178	0.651	0.651	0.154	0.154
Year-month FE	No	No	No	No	No	No
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes

Note: Column (1) regresses an indicator for a nonbank (multiplied by 100) on observable risk while controlling for year-month fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Column (2) is similar except including ZIP code by year-quarter fixed effects and adding the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Column (3) is analogous except that the dependent variable is the interest rate net of g-fees and we add the nonbank indicator. Column (4) is similar to column (3) except adding the interaction between the nonbank indicator and observable risk. Columns (5) and (6) are analogous to (3) and (4) except that the dependent variable is an indicator for default (multiplied by 100). T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Appendix

A Proof of equations (6) and (7)

To derive the first order condition for r_j^z, first observe that by using $\delta^L = 0$ and $\delta^M = \frac{q}{1+q}$ it is convenient to write lender profits as

$$\Pi_j = \sum_z \frac{\psi_j^{1_{\{z=L\}}}(1-\psi_j)^{1_{\{z=M\}}}}{1-\delta^z} s_j^z\left(r_j^z(1-\delta^z) - (\rho + \omega\delta^z)\right) - c(\psi_j) \tag{9}$$

Then the first order condition for r_j^z is

$$\begin{aligned}
0 &= \frac{\partial \Pi_j}{\partial r_j^z} \\
&\propto \frac{\partial s_j^z}{\partial r_j^z}\left(r_j^z(1-\delta^z) - (\rho+\omega\delta^z)\right) + s_j(1-\delta^z) \\
&= \left[\frac{-\alpha \exp(\mu - \alpha r_j^z) - (-\alpha \exp(\mu - \alpha r_j^z)\exp(\mu - \alpha r_j^z))}{\left(1 + \sum_{k=1}^n \exp(\mu - \alpha r_k^z)\right)^2}\right]\left(r_j^z(1-\delta^z) - (\rho+\omega\delta^z)\right) \\
&\quad + s_j^z(1-\delta^z) \\
&= \left[-\alpha s_j^z(1-s_j^z)\right]\left(r_j^z(1-\delta^z) - (\rho+\omega\delta^z)\right) + s_j^z(1-\delta^z) \\
\implies r_j^z &= \frac{\rho+\omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s_j^z)}.
\end{aligned} \tag{10}$$

Differentiating lender profits as written in equation (5) by ψ_j yields

$$\begin{aligned}
0 &= \frac{\partial \Pi_j}{\partial \psi_j} \\
&= s_j^L(r_j^L - \rho) - (1+q)s_j^M\left(r_j^M(1-\delta^M) - (\rho+\omega\delta^M)\right) - c'(\psi_j) \\
\implies c'(\psi_j) &= s_j^L(r_j^L - \rho) - (1+q)s_j^M\left(r_j^M(1-\delta^M) - (\rho+\omega\delta^M)\right).
\end{aligned} \tag{11}$$

By substituting in r_j^z from equation (6), this can also be written as

$$c'(\psi_j) = \frac{s_j^L}{\alpha(1-s_j^L)} - \frac{s_j^M}{\alpha(1-s_j^M)}. \tag{12}$$

Internet appendix

This Internet Appendix contains the following supplemental material:

1. Appendix B provides supplementary material for the institutional background and data.
   (a) Table B.1 shows summary statistics for the 2016-2017 sample of originations from the Mortgage Loan Information System (provided by Fannie Mae and Freddie Mac).
   (b) Table B.2 shows summary statistics for the 2018 sample of originations from the Mortgage Loan Information System (provided by Fannie Mae and Freddie Mac) merged with HMDA.
2. Appendix C provides supplementary material for the empirical observations (Section 3)
   (a) Figure C.1 shows the average, the 10th percentile, and the 90th percentile of the spread of interest rates net of g-fees relative to the best available rates as a function of observable risk and shifted to start at zero for low observable risk.
   (b) Figure C.2 shows the average, the 10th percentile, and the 90th percentile of the spread of interest rates net of g-fees relative to the best available rates as a function of observable risk and for a subsample of mortgages that are relatively straightforward to underwrite.
   (c) Figure C.3 shows origination revenue and its components as a function of observable risk.
   (d) Table C.3 estimates the association between origination revenue (and its components) and observable risk.
   (e) Table C.4 estimates the association between interest rates and observable risk when using data from Optimal Blue and controlling for lock date fixed effects while restricting to government-insured loans.
   (f) Table C.5 estimates the association between observable risk and measures of shopping and financial knowledge.
   (g) Table C.6 estimates the association between interest rates and observable risk while controlling for observable prepayment risk.
   (h) Figure C.4 shows the association between default and origination revenue with and without controlling for observable risk.
   (i) Table C.7 estimates the association between default and origination revenue with and without controlling for observable risk.
   (j) Table C.8 estimates the association between interest rates and default while controlling for observable risk and observable prepayment risk.
   (k) Figure C.5 shows the residual association between the interest rate and the upfront g-fee after controlling for observable risk.

(l) Table C.9 shows how interest rates and defaults vary across thresholds in the upfront g-fee.

(m) Table C.10 shows the fraction of denials attributable to various reasons.

(n) Figure C.6 shows the association between denials and observable risk after omitting various denial reasons.

3. Appendix D provides supplementary material for the model (Sections 4 and 5)

   (a) Appendix D.1 compares the total surplus and its components for active and passive intermediation.

   (b) Figure D.2 shows how the active intermediation equilibrium varies with the expected loss given default ω.

   (c) Figure D.3 shows how the active intermediation equilibrium varies with the number of lenders n.

4. Appendix E provides supplementary material for the analysis of heterogeneous lenders (Section 6)

   (a) Figure E.1 shows the kernel density and cumulative distribution function of observable risk for different types of lenders.

   (b) Figure E.2 shows the distributions of observable risk and constituent underwriting characteristics for different types of lenders.

   (c) Table E.1 shows summary statistics for observable and its contributing factors for banks, nonbank non-fintechs, and fintechs.

   (d) Table E.2 estimates the association between origination revenue (and its components) with observable risk and lender type.

   (e) Table E.3 estimates the associations between nonbanks and observable risk, interest rates, and default while splitting nonbanks by fintechs and nonfintechs.

   (f) Figure E.3 shows the association between nonbanks and observable risk, interest rates, and default over time.

   (g) Table E.4 estimates the association between nonbank market share and observable risk over time.

   (h) Table E.5 estimates the association between interest rates net of g-fees and nonbanks over time.

   (i) Table E.6 estimates the association between default and nonbanks over time.

   (j) Table E.7 estimates the association between nonbanks and borrower self-assessed risk and borrower satisfaction.

   (k) Figure E.4 qualitatively emulates the change over time for banks and nonbanks.

5. Appendix F describes an alternative model featuring strategic interactions between lenders.

6. Appendix G describes the results of the alternative model.

7. Appendix H describes versions of the alternative model with heterogeneous lenders.
8. Appendix I provides proofs and supplementary material for the alternative model (Appendix F).
   (a) Figure I.1 shows the posterior risk conditional on one signal.
   (b) Subsection I.2 proves Proposition F.1.
   (c) Subsection I.3 computes equation (F.4).
   (d) Subsection I.4 proves Proposition F.2.
   (e) Subsection I.5 computes a lender's expected profits.
   (f) Subsection I.6 computes a consumer's expected surplus.
9. Appendix J provides results and supplementary material for the alternative model simulation (Appendix G).
   (a) Figure J.1 compares active and passive intermediation.
   (b) Figure J.2 compares the surplus for active and passive intermediation.
10. Appendix K provides results and supplementary material for the versions of the alternative model with heterogeneous lenders (Appendix H).
    (a) Subsection K.1 computes equation (H.2).
    (b) Subsection K.2 proves Proposition H.1.
    (c) Subsection K.3 proves Proposition H.2.
    (d) Subsection K.4 proves Proposition H.3.
    (e) Subsection K.5 proves Proposition H.4.
    (f) Figure K.1 shows active intermediation with heterogeneous ψ.
    (g) Figure K.2 shows active intermediation with heterogeneous ω.

B Supplemental material for the data description (Section 2.2)

Table B.1: Summary statistics for the 2016-2017 sample

(a) Full sample

	N	Mean	SD	P25	P75
Default (%)	875,468	0.50	7.09	0.00	0.00
Credit score	875,468	749.41	47.86	717.00	789.00
Loan-to-value (%)	875,468	69.94	13.42	64.00	80.00
Debt-to-income (%)	875,468	33.53	9.89	26.00	41.65
Observable risk (%)	875,468	0.50	0.77	0.12	0.46
Interest rate (%)	875,468	3.94	0.35	3.62	4.17
G-fee (%)	875,468	0.51	0.12	0.44	0.53
Bank	875,468	0.58	0.49	0.00	1.00
Nonbank-nonfintech	875,468	0.36	0.48	0.00	1.00
Nonbank-fintech	875,468	0.06	0.24	0.00	0.00
Income ($1000s)	875,464	76.92	44.13	45.50	97.03
Single female	875,468	0.21	0.41	0.00	0.00
Single male	875,468	0.27	0.45	0.00	1.00
> 1 borrower	875,468	0.51	0.50	0.00	1.00
Hispanic	875,468	0.08	0.27	0.00	0.00
Black	875,468	0.02	0.14	0.00	0.00
Term (months)	875,468	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	875,468	343.96	166.29	217.00	445.00
Refinance	875,468	0.41	0.49	0.00	1.00

Note: These tables present summary statistics for the 2016-2017 sample (Table B.1a), the subsample of loans originated by banks (Table B.1b), the subsample of loans originated by nonbank-nonfintechs (Table B.1c), and the subsample of loans originated by fintechs (Table B.1d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the respective present value multiplier before being added to the ongoing component of the g-fee. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and > 1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.1: Summary statistics (continued)

(b) Banks

	N	Mean	SD	P25	P75
Default (%)	509,099	0.38	6.13	0.00	0.00
Credit score	509,099	752.56	46.53	722.00	790.00
Loan-to-value (%)	509,099	70.30	13.43	64.00	80.00
Debt-to-income (%)	509,099	32.87	9.90	25.25	41.05
Observable risk (%)	509,099	0.45	0.71	0.10	0.42
Interest rate (%)	509,099	3.91	0.34	3.62	4.12
G-fee (%)	509,099	0.50	0.12	0.44	0.53
Income ($1000s)	509,097	77.61	44.86	45.55	98.11
Single female	509,099	0.21	0.41	0.00	0.00
Single male	509,099	0.26	0.44	0.00	1.00
>1 borrower	509,099	0.53	0.50	0.00	1.00
Hispanic	509,099	0.07	0.25	0.00	0.00
Black	509,099	0.02	0.13	0.00	0.00
Term (months)	509,099	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	509,099	332.77	163.26	210.00	430.00
Refinance	509,099	0.38	0.48	0.00	1.00

Note: These tables present summary statistics for the 2016-2017 sample (Table B.1a), the subsample of loans originated by banks (Table B.1b), the subsample of loans originated by nonbank-nonfintechs (Table B.1c), and the subsample of loans originated by fintechs (Table B.1d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the respective present value multiplier before being added to the ongoing component of the g-fee. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.1: Summary statistics (continued)

(c) Nonbank-nonfintechs

	N	Mean	SD	P25	P75
Default (%)	311,215	0.67	8.13	0.00	0.00
Credit score	311,215	745.79	48.79	711.00	787.00
Loan-to-value (%)	311,215	69.61	13.42	63.00	80.00
Debt-to-income (%)	311,215	34.46	9.78	27.15	42.40
Observable risk (%)	311,215	0.55	0.83	0.12	0.58
Interest rate (%)	311,215	3.98	0.37	3.75	4.25
G-fee (%)	311,215	0.52	0.13	0.45	0.54
Income ($1000s)	311,214	76.26	43.10	45.83	95.83
Single female	311,215	0.22	0.42	0.00	0.00
Single male	311,215	0.29	0.45	0.00	1.00
>1 borrower	311,215	0.49	0.50	0.00	1.00
Hispanic	311,215	0.10	0.30	0.00	0.00
Black	311,215	0.02	0.15	0.00	0.00
Term (months)	311,215	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	311,215	365.74	169.91	235.00	475.00
Refinance	311,215	0.44	0.50	0.00	1.00

Note: These tables present summary statistics for the 2016-2017 sample (Table B.1a), the subsample of loans originated by banks (Table B.1b), the subsample of loans originated by nonbank-nonfintechs (Table B.1c), and the subsample of loans originated by fintechs (Table B.1d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the respective present value multiplier before being added to the ongoing component of the g-fee. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.1: Summary statistics (continued)

(d) Fintechs

	N	Mean	SD	P25	P75
Default (%)	55,154	0.78	8.79	0.00	0.00
Credit score	55,154	740.79	52.00	702.00	786.00
Loan-to-value (%)	55,154	68.53	13.25	61.00	80.00
Debt-to-income (%)	55,154	34.32	9.94	26.87	42.34
Observable risk (%)	55,154	0.63	0.92	0.12	0.68
Interest rate (%)	55,154	4.04	0.34	3.75	4.25
G-fee (%)	55,154	0.52	0.13	0.44	0.56
Income ($1000s)	55,153	74.19	42.80	43.35	94.17
Single female	55,154	0.21	0.40	0.00	0.00
Single male	55,154	0.27	0.44	0.00	1.00
>1 borrower	55,154	0.52	0.50	0.00	1.00
Hispanic	55,154	0.06	0.24	0.00	0.00
Black	55,154	0.03	0.17	0.00	0.00
Term (months)	55,154	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	55,154	324.41	160.59	200.00	420.00
Refinance	55,154	0.62	0.49	0.00	1.00

Note: These tables present summary statistics for the 2016-2017 sample (Table B.1a), the subsample of loans originated by banks (Table B.1b), the subsample of loans originated by nonbank-nonfintechs (Table B.1c), and the subsample of loans originated by fintechs (Table B.1d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the respective present value multiplier before being added to the ongoing component of the g-fee. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.2: Summary statistics for the 2018 sample

(a) Full sample

	N	Mean	SD	P25	P75
Default (%)	162,561	2.01	14.04	0.00	0.00
Credit score	162,561	745.80	49.12	712.00	787.00
Loan-to-value (%)	162,561	69.50	14.25	62.00	80.00
Debt-to-income (%)	162,561	35.75	9.93	28.26	44.30
Observable risk (%)	162,561	0.59	0.89	0.12	0.59
Interest rate (%)	162,561	4.69	0.39	4.38	4.88
G-fee (%)	162,561	0.51	0.14	0.43	0.54
Bank	162,561	0.55	0.50	0.00	1.00
Nonbank-nonfintech	162,561	0.38	0.48	0.00	1.00
Nonbank-fintech	162,561	0.07	0.25	0.00	0.00
Income ($1000s)	162,561	76.97	43.41	45.69	97.50
Single female	162,561	0.22	0.42	0.00	0.00
Single male	162,561	0.28	0.45	0.00	1.00
>1 borrower	162,561	0.49	0.50	0.00	1.00
Hispanic	162,561	0.09	0.28	0.00	0.00
Black	162,561	0.02	0.15	0.00	0.00
Term (months)	162,561	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	162,561	343.15	149.90	226.90	445.00
Refinance	162,561	0.27	0.44	0.00	1.00
Origination revenue (%)	162,561	3.98	1.84	2.75	5.02
Closing costs (%)	162,561	0.77	0.81	0.27	1.12
Secondary marketing income (%)	162,561	3.22	1.63	2.17	4.19

Note: These tables present summary statistics for the 2018 sample (Table B.2a), the subsample of loans originated by banks (Table B.2b), the subsample of loans originated by nonbank-nonfintechs (Table B.2c), and the subsample of loans originated by fintechs (Table B.2d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the GSE's respective present value multiplier before being added to the ongoing component of the g-fee. *Origination revenue* is origination charges plus secondary marketing income (as defined in Section 2.1) divided by the loan amount. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. *Origination revenue* is a lender's income from originating a loan net of lender credits, expressed as a percentage of the loan amount (see Section 2.1). *Closing costs* is origination charges as a percentage of the loan amount. *Secondary marketing income* is the present value of the deviation of a loan's interest rate net of g-fees relative to par, which we compute by subtracting the current coupon yield on GSE-guaranteed mortgage-backed securities as of the origination date from the interest rate net of the total g-fee and multiplying by the loan's estimated present value multiplier. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.2: Summary statistics for the 2018 sample (continued)

(b) Banks

	N	Mean	SD	P25	P75
Default (%)	90,194	2.08	14.27	0.00	0.00
Credit score	90,194	749.08	48.20	717.00	788.00
Loan-to-value (%)	90,194	69.62	14.34	62.00	80.00
Debt-to-income (%)	90,194	35.21	9.97	27.66	43.76
Observable risk (%)	90,194	0.54	0.84	0.12	0.49
Interest rate (%)	90,194	4.65	0.38	4.38	4.88
G-fee (%)	90,194	0.50	0.13	0.42	0.53
Income ($1000s)	90,194	77.99	44.07	46.00	99.14
Single female	90,194	0.22	0.42	0.00	0.00
Single male	90,194	0.28	0.45	0.00	1.00
>1 borrower	90,194	0.50	0.50	0.00	1.00
Hispanic	90,194	0.08	0.27	0.00	0.00
Black	90,194	0.02	0.15	0.00	0.00
Term (months)	90,194	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	90,194	338.24	149.41	225.00	436.10
Refinance	90,194	0.25	0.43	0.00	0.00
Origination revenue (%)	90,194	3.70	1.71	2.58	4.70
Closing costs (%)	90,194	0.67	0.71	0.25	0.99
Secondary marketing income (%)	90,194	3.03	1.54	2.04	3.97

Note: These tables present summary statistics for the 2018 sample (Table B.2a), the subsample of loans originated by banks (Table B.2b), the subsample of loans originated by nonbank-nonfintechs (Table B.2c), and the subsample of loans originated by fintechs (Table B.2d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the GSE's respective present value multiplier before being added to the ongoing component of the g-fee. *Origination revenue* is origination charges plus secondary marketing income (as defined in Section 2.1) divided by the loan amount. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. *Origination revenue* is a lender's income from originating a loan net of lender credits, expressed as a percentage of the loan amount (see Section 2.1). *Closing costs* is origination charges as a percentage of the loan amount. *Secondary marketing income* is the present value of the deviation of a loan's interest rate net of g-fees relative to par, which we compute by subtracting the current coupon yield on GSE-guaranteed mortgage-backed securities as of the origination date from the interest rate net of the total g-fee and multiplying by the loan's estimated present value multiplier. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.2: Summary statistics for the 2018 sample (continued)

(c) Nonbank-nonfintechs

	N	Mean	SD	P25	P75
Default (%)	61,226	1.92	13.73	0.00	0.00
Credit score	61,226	743.14	49.16	709.00	784.00
Loan-to-value (%)	61,226	69.63	14.09	63.00	80.00
Debt-to-income (%)	61,226	36.47	9.83	29.18	44.96
Observable risk (%)	61,226	0.63	0.92	0.13	0.65
Interest rate (%)	61,226	4.75	0.40	4.50	5.00
G-fee (%)	61,226	0.52	0.14	0.44	0.55
Income ($1000s)	61,226	76.00	42.43	45.57	95.87
Single female	61,226	0.23	0.42	0.00	0.00
Single male	61,226	0.29	0.46	0.00	1.00
>1 borrower	61,226	0.48	0.50	0.00	1.00
Hispanic	61,226	0.10	0.30	0.00	0.00
Black	61,226	0.02	0.16	0.00	0.00
Term (months)	61,226	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	61,226	353.41	149.47	235.20	455.00
Refinance	61,226	0.27	0.44	0.00	1.00
Origination revenue (%)	61,226	4.23	1.88	2.95	5.28
Closing costs (%)	61,226	0.78	0.84	0.28	1.17
Secondary marketing income (%)	61,226	3.45	1.65	2.37	4.44

Note: These tables present summary statistics for the 2018 sample (Table B.2a), the subsample of loans originated by banks (Table B.2b), the subsample of loans originated by nonbank-nonfintechs (Table B.2c), and the subsample of loans originated by fintechs (Table B.2d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the GSE's respective present value multiplier before being added to the ongoing component of the g-fee. *Origination revenue* is origination charges plus secondary marketing income (as defined in Section 2.1) divided by the loan amount. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. *Origination revenue* is a lender's income from originating a loan net of lender credits, expressed as a percentage of the loan amount (see Section 2.1). *Closing costs* is origination charges as a percentage of the loan amount. *Secondary marketing income* is the present value of the deviation of a loan's interest rate net of g-fees relative to par, which we compute by subtracting the current coupon yield on GSE-guaranteed mortgage-backed securities as of the origination date from the interest rate net of the total g-fee and multiplying by the loan's estimated present value multiplier. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table B.2: Summary statistics for the 2018 sample (continued)

(d) Fintechs

	N	Mean	SD	P25	P75
Default (%)	11,141	1.98	13.94	0.00	0.00
Credit score	11,141	733.84	53.40	693.00	781.00
Loan-to-value (%)	11,141	67.89	14.24	60.00	80.00
Debt-to-income (%)	11,141	36.18	9.90	28.54	44.81
Observable risk (%)	11,141	0.77	1.06	0.14	0.94
Interest rate (%)	11,141	4.72	0.41	4.38	4.88
G-fee (%)	11,141	0.49	0.15	0.40	0.53
Income ($1000s)	11,141	74.08	43.06	42.64	94.34
Single female	11,141	0.22	0.41	0.00	0.00
Single male	11,141	0.29	0.45	0.00	1.00
>1 borrower	11,141	0.49	0.50	0.00	1.00
Hispanic	11,141	0.07	0.26	0.00	0.00
Black	11,141	0.04	0.19	0.00	0.00
Term (months)	11,141	360.00	0.00	360.00	360.00
Appraisal value ($1000s)	11,141	326.52	152.75	205.00	425.00
Refinance	11,141	0.48	0.50	0.00	1.00
Origination revenue (%)	11,141	4.90	2.12	3.35	6.19
Closing costs (%)	11,141	1.42	1.11	0.46	2.29
Secondary marketing income (%)	11,141	3.48	1.91	2.14	4.62

Note: These tables present summary statistics for the 2018 sample (Table B.2a), the subsample of loans originated by banks (Table B.2b), the subsample of loans originated by nonbank-nonfintechs (Table B.2c), and the subsample of loans originated by fintechs (Table B.2d). *Default* indicates 90-day delinquency within 2 years of origination (multiplied by 100). *Credit score* is the representative credit score, i.e., the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three. *Loan-to-value* (LTV) is the ratio of the loan amount to the lesser of the appraised value and the selling price. *Debt-to-income* (DTI) is the ratio of all debt payments to household income. *Observable risk* is the estimated probability of default based on credit score, LTV, and DTI as described in Section 2.1. *Interest rate* is the interest rate at origination. *G-fee* is the total guarantee fee expressed as an annualized rate. Note that the upfront component of the g-fee is converted to an annualized rate using the GSE's respective present value multiplier before being added to the ongoing component of the g-fee. *Origination revenue* is origination charges plus secondary marketing income (as defined in Section 2.1) divided by the loan amount. *Bank* is an indicator for depositories. *Nonbank-nonfintech* is an indicator for lenders that are neither banks nor fintechs. *Fintech* is an indicator for lenders with a mostly online application process based on the designation of fintechs in Buchak et al. (2018)). *Income* is the gross income of all borrowers. *Single female*, *single male*, and >1 *borrower* indicate the number of borrowers and, in the case of 1 borrower, the gender. *Hispanic* and *Black* refer to the ethnicity and race of the primary borrower. *Term* is the number of monthly payments from the origination date until the maturity date of the loan specified as of the origination date. *Appraisal value* is the appraised value of the collateral for the mortgage. *Refinance* indicates refinance loans. *Origination revenue* is a lender's income from originating a loan net of lender credits, expressed as a percentage of the loan amount (see Section 2.1). *Closing costs* is origination charges as a percentage of the loan amount. *Secondary marketing income* is the present value of the deviation of a loan's interest rate net of g-fees relative to par, which we compute by subtracting the current coupon yield on GSE-guaranteed mortgage-backed securities as of the origination date from the interest rate net of the total g-fee and multiplying by the loan's estimated present value multiplier. Continuous variables are winsorized at 1%. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

C Supplemental material for the empirical findings (Section 3)

C.1 Supplemental material for Section 3.1

Figure C.1: Interest rates and observable risk: average and dispersion (shifted)

This figure shows the 10th percentile, the 90th percentile, and the average of the spread of the interest rate net of the total g-fee relative to the best available rate for deciles of observable risk. The series have been shifted so that each starts at zero for borrowers with the lowest observable risk. The best available rate is determined by computing the 10th percentile of the interest rate net of the total g-fee for the borrowers in the lowest quartile of observable risk in each week. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

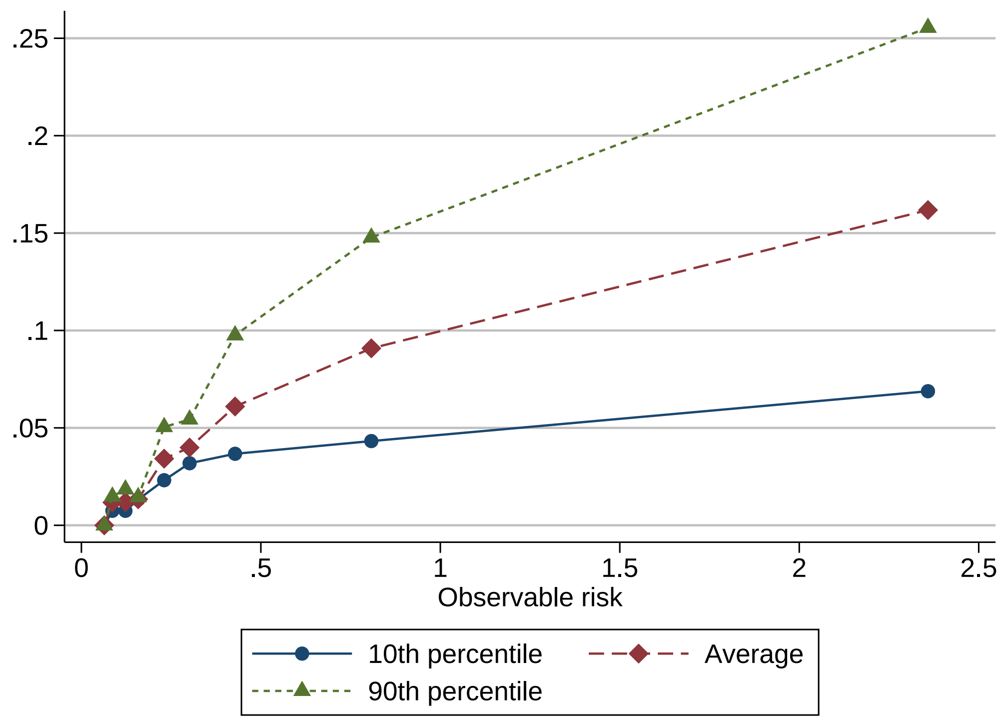


Figure C.2: Interest rates and observable risk: average and dispersion (subsample)

This figure shows the 10th percentile, 90th percentile, and average of the spread of the interest rate net of the total g-fee relative to the best available rate for deciles of observable risk. The best available rate is determined by computing the 10th percentile of the interest rate net of the total g-fee for the borrowers in the lowest quartile of observable risk in each week. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points. We further restrict to a set of mortgages that are relatively straightforward to underwrite: (no cash-out) refinance mortgages where no borrowers are self-employed, there is full income and asset documentation, the LTV ratio is no greater than 70%, and the loan amount is greater than the 25th percentile (about $146,000).

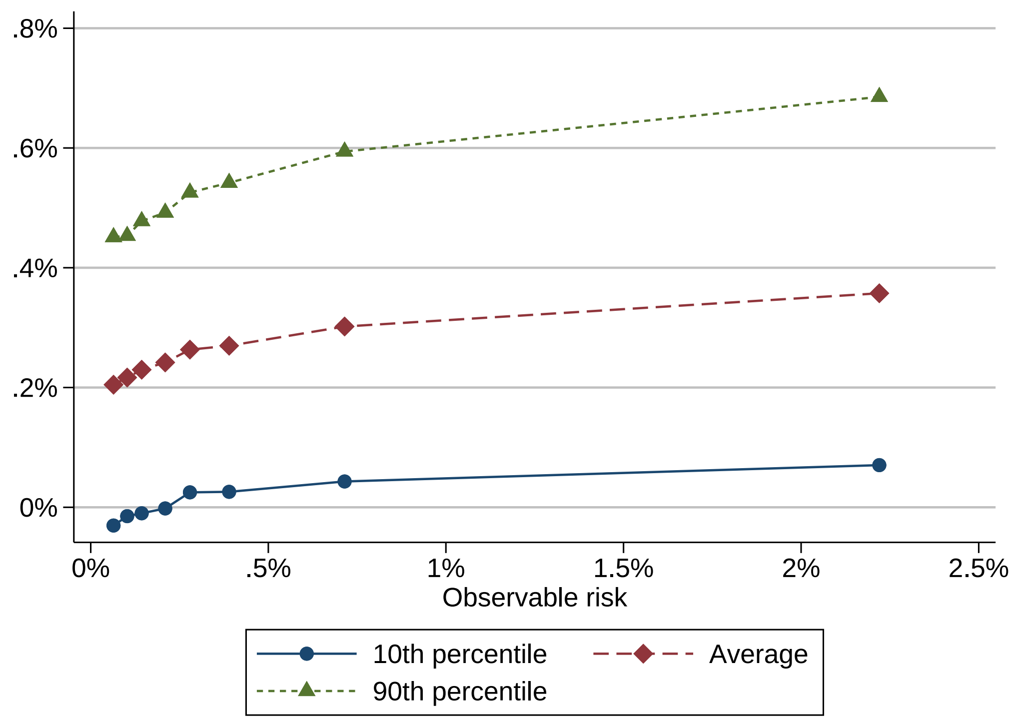


Figure C.3: Origination revenue components and observable risk

This figure presents a binned scatterplot of origination revenue components (closing costs and secondary marketing income as a percentage of the loan amount) on observable risk while controlling for year-month fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

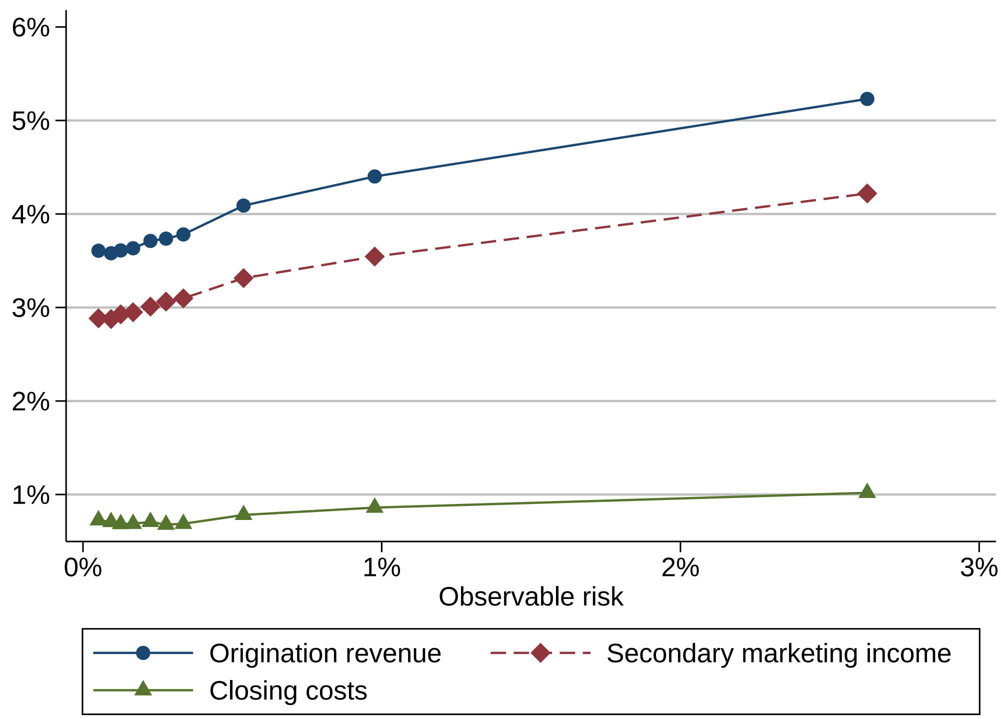


Table C.3: Origination revenue and observable risk

	(1) Orig. rev.	(2) Orig. rev.	(3) Closing costs	(4) Closing costs	(5) Second. income	(6) Second. income
Observable risk	0.442***		0.078***		0.367***	
	(94.08)		(25.99)		(77.35)	
Credit score		-0.726***		-0.127***		-0.608***
		(-90.52)		(-22.58)		(-75.05)
LTV		1.128***		0.012		1.111***
		(34.82)		(0.44)		(34.51)
DTI		0.669***		0.126***		0.545***
		(17.77)		(5.49)		(14.36)
Observations	162,561	162,561	162,561	162,561	162,561	162,561
R^2	0.620	0.622	0.378	0.377	0.508	0.512
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Column (1) regresses origination revenue on observable risk while controlling for ZIP code by year-quarter fixed effects, seller by year-quarter fixed effects, and the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Column (2) regresses origination revenue on credit score, the loan-to-value (LTV) ratio, and the debt-to-income (DTI) ratio (each divided by 100). Column (3) and column (4) are similar to column (1) and column (2) except that the dependent variable is the closing costs portion of origination revenue. Column (5) and column (6) are similar to column (1) and column (2) except that the dependent variable is the secondary marketing income portion of origination revenue. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table C.4: Interest rates and observable risk with lock date fixed effects for government-insured loans

	(1) IR	(2) IR
Credit score	-0.279***	-0.115***
	(-323.07)	(-30.17)
LTV	0.277***	-0.401***
	(42.81)	(-25.05)
DTI	0.160***	0.170***
	(38.57)	(41.49)
Observations	640,733	640,733
R^2	0.387	0.417
Lock Date FE	Yes	Yes
Credit score-LTV FE	No	Yes

Note: Column (1) regresses the interest rate on credit score, the loan-to-value (LTV) ratio, and the debt-to-income (DTI) ratio (each divided by 100). Column (2) is similar except including fixed effects for grid cells in credit score and LTV corresponding to the first table of the GSEs' g-fee matrix. Note that the fixed effects in column (2) are only for purposes of comparison to GSE loans but do not correspond to actual g-fees, as g-fees do not apply to loans insured by government agencies. Source: Optimal Blue rate lock data, 2016-2017, restricting to fixed rate, purchase or no cash-out refinance loans insured by FHA, VA, or USDA for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table C.5: Financial sophistication and observable risk

	(1) Multiple lenders	(2) Acquired info	(3) Financial knowledge	(4) Concerned
Observable risk	-0.007	-0.013	-0.189***	0.076***
	(-0.28)	(-0.63)	(-3.87)	(5.10)
Observations	4,408	4,408	4,408	4,408
R^2	0.165	0.164	0.170	0.180
State $\times$ Year-quarter FE	Yes	Yes	Yes	Yes

Note: Column (1) regresses an indicator for seriously considering or applying to at least 2 lenders on observable risk and state by year-quarter fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1 (computing observable risk within the NMDB sample). Column (2) is similar except that the dependent variable is an indicator for obtaining information from other lenders, the internet, or friends, relatives, or coworkers on observable risk. Column (3) is similar except that the dependent variable is an index of mortgage knowledge as described in Section 3.1, normalized to have a standard deviation of 1. Column (4) is similar except that the dependent variable is in indicator for a borrower that applies to multiple lenders due to concern over qualifying for a loan. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: National Survey of Mortgage Originations, 2013-2017, restricting to GSE-acquired, fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, site-built properties and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%.

Table C.6: Interest rates, observable risk, and observable prepayment risk

	(1) IR	(2) IR	(3) IR - g-fee
Observable risk	0.150***	0.156***	0.033***
	(263.25)	(263.82)	(71.01)
Obs. prepayment risk	0.001***	-0.004***	0.007***
	(6.00)	(-19.38)	(34.35)
Observations	875,464	875,464	875,464
R^2	0.674	0.681	0.697
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes
Seller $\times$ Year-quarter FE	Yes	Yes	Yes
Controls	No	Yes	Yes

Note: Column (1) regresses the interest rate on observable risk and observable prepayment risk while controlling for ZIP code by year-quarter fixed effects and seller by year-quarter fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Observable prepayment risk is defined analogously but based on prepayment within 2 years and including decile indicators for the loan amount as predictors. Column (2) adds the following controls: loan amount decile indicators and an indicator for full asset and income documentation. Column (3) is similar to column (2) except that the dependent variable is the interest rate net of the total g-fee. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

C.2 Supplemental material for Section 3.2

Figure C.4: Origination revenue and default

This figure presents a binned scatterplot of default (multiplied by 100) on origination revenue while controlling for year-month fixed effects and observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Note that for loans originated in 2018 we only consider defaults within one year of origination to avoid unusual activity associated with the COVID-19 pandemic and the associated ease of forbearance. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

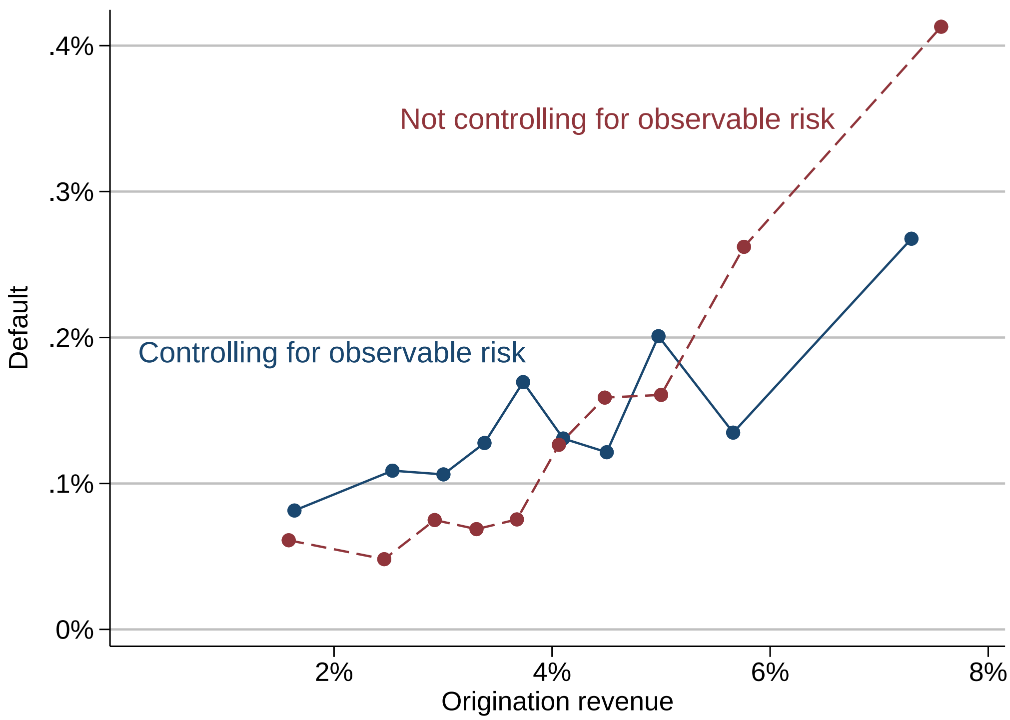


Table C.7: Origination revenue and default

	(1) Default	(2) Default	(3) Default	(4) Default	(5) Default	(6) Default
Origination revenue	0.079***	0.043***	0.043***	0.007	0.058***	0.007
	(8.35)	(4.81)	(4.30)	(1.19)	(3.61)	(1.20)
Observable risk		0.234***		0.271*	0.223***	0.271*
		(9.06)		(1.75)	(6.85)	(1.77)
Origination revenue × Risky						0.050***
						(2.91)
Observable risk × Risky						-0.047
						(-0.30)
Observations	162,561	162,561	162,561	66,040	80,349	146,389
R^2	0.236	0.238	0.248	0.395	0.305	0.316
ZIP × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	No
ZIP × Year-quarter × Risky FE	No	No	No	No	No	Yes
Seller × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	No
Seller × Year-quarter × Risky FE	No	No	No	No	No	Yes
Controls	No	No	Yes	No	No	No
Sample	Full	Full	Full	Safe	Risky	Full

Note: Column (1) regresses an indicator for default (multiplied by 100) on the origination revenue while controlling for ZIP code by year-quarter fixed effects and seller by year-quarter fixed effects. Note that for loans originated in 2018 we only consider defaults within one year of origination to avoid unusual activity associated with the COVID-19 pandemic and the associated ease of forbearance. Column (2) adds observable risk as a regressor. Column (3) instead includes the following controls: the interaction between 10-point credit score bins (starting at 620, with an additional indicator for all credit scores below 620), 5% loan-to-value bins (starting at 60%, with an additional indicator for all loan-to-value ratios below 60%), and debt-to-income decile indicators (note that this interaction absorbs observable risk); loan amount decile indicators; an indicator for full income and asset documentation; income decile indicators; family type indicators (i.e., single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; appraisal value decile indicators; an indicator for a refinance loan; an indicator for self-employed borrowers; and an indicator for first-time homebuyers. Column (4) estimates the specification in column (2) except restricting to relatively safe borrowers with observable risk below the median. Column (5) estimates the specification in column (2) except restricting to relatively risky borrowers with observable risk above the median. Column (6) estimates the specification in column (2) except interacting all the regressors with a dummy variable *Risky* indicating borrowers with observable risk above the median. Column (7) estimates the specification in column (2) except using the interest rate (without subtracting out the g-fee) as the dependent variable. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table C.8: Interest rates, default, and prepayment risk

	(1) Default	(2) Default	(3) Default
IR - g-fee	0.435***	0.075**	0.608***
	(8.98)	(2.30)	(6.89)
Observable risk	0.959***	0.900***	0.950***
	(31.90)	(6.53)	(26.38)
Obs. prepayment risk	-0.025***	-0.012*	-0.020
	(-2.76)	(-1.94)	(-1.44)
Observations	875,464	409,879	426,296
R^2	0.163	0.230	0.223
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes
Seller $\times$ Year-quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Sample	Full	Safe	Risky

Note: Column (1) regresses an indicator for default (multiplied by 100) on the interest rate net of the total g-fee, observable risk, and observable prepayment risk while controlling for ZIP code by year-quarter fixed effects, seller by year-quarter fixed effects, and the following controls: loan amount decile indicators and an indicator for full asset and income documentation. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Observable prepayment risk is defined analogously but based on prepayment within 2 years and including decile indicators for the loan amount as predictors. Column (2) estimates the specification in column (1) except restricting to relatively safe borrowers with observable risk below the median. Column (3) estimates the specification in column (1) except restricting to relatively risky borrowers with observable risk above the median. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Figure C.5: G-fee induced variation in interest rates

This figure presents a binned scatterplot of the interest rate on the upfront g-fee while controlling for origination year-month fixed effects and observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix.

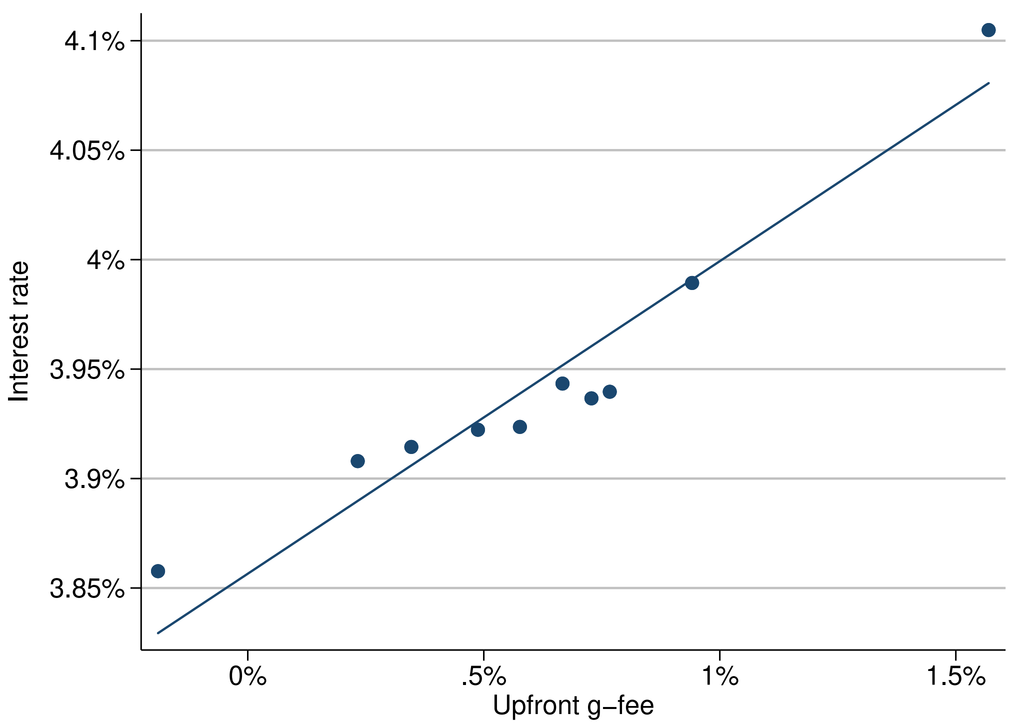


Table C.9: Interest rates and defaults at each g-fee threshold

(a) Interest rates

	(1) IR	(2) IR	(3) IR	(4) IR	(5) IR	(6) IR	(7) IR
Above threshold	-0.103***	-0.091**	-0.172***	-0.071***	-0.181***	-0.089***	-0.083***
	(-4.78)	(-2.52)	(-6.53)	(-4.11)	(-14.47)	(-9.51)	(-10.54)
Observations	2,464	965	1,643	2,846	6,940	10,615	12,819
R^2	0.454	0.394	0.458	0.499	0.459	0.484	0.525
Credit score threshold	680	660	680	720	680	700	720
LTV range	60-70	70-75	70-75	70-75	75-80	75-80	75-80
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LTV FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(b) Defaults

	(1) Default	(2) Default	(3) Default	(4) Default	(5) Default	(6) Default	(7) Default
Above threshold	-1.407	-0.516	0.618	-0.618	0.360	0.463	-0.067
	(-1.59)	(-0.25)	(0.58)	(-1.28)	(0.68)	(1.31)	(-0.27)
Observations	2,464	965	1,643	2,846	6,940	10,615	12,819
R^2	0.012	0.019	0.018	0.010	0.004	0.004	0.003
Credit score threshold	680	660	680	720	680	700	720
LTV range	60-70	70-75	70-75	70-75	75-80	75-80	75-80
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LTV FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column of Table C.9a restricts to loans with a credit score within 5 points of the indicated threshold and loan-to-value (LTV) ratio in the indicated range. Each column regresses the interest rate on an indicator for having a credit score greater than or equal to the respective threshold while controlling for the credit score (minus the respective threshold), year-month fixed effects, and LTV (rounded to the nearest integer) fixed effects. Table C.9b is similar except that the dependent variable is an indicator for default (multiplied by 100). T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, loans with debt-to-income ratio up to 43%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix.

C.3 Supplemental material for Section 3.3

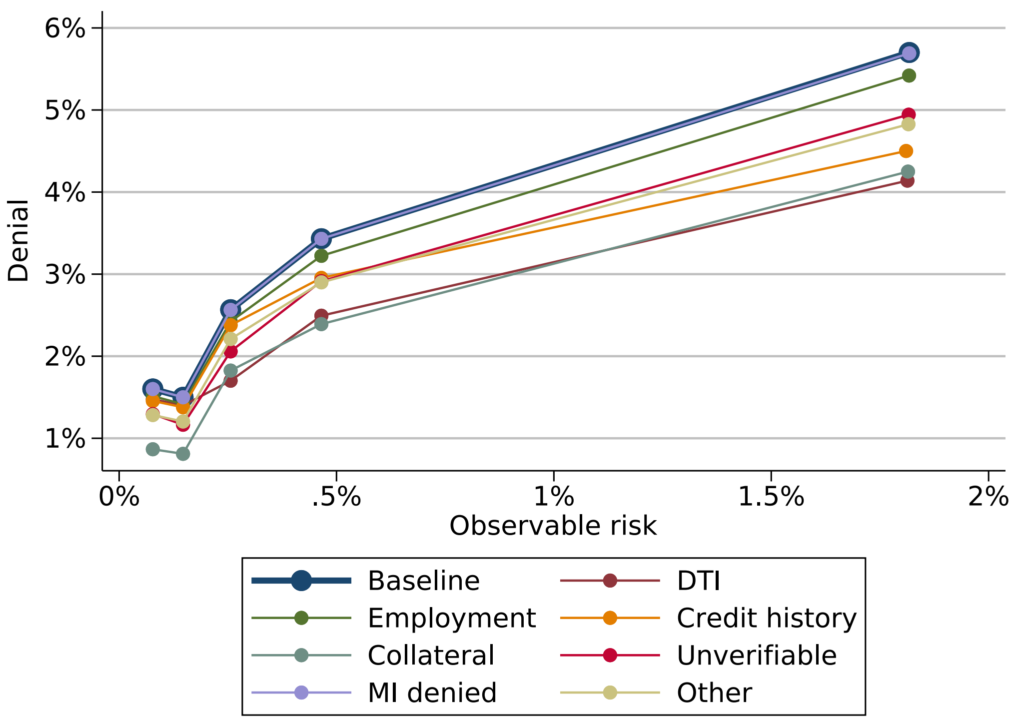
Table C.10: Denial reasons for loans accepted by GSE AUS

Denial reason	Count	Percent
Debt-to-income ratio	4,912	12.62
Employment history	766	1.96
Credit history	2,820	7.24
Collateral	6,997	17.98
Insufficient cash (downpayment, closing costs)	2,107	5.41
Unverifiable information	3,134	8.05
Credit application incomplete	14,4963	38.46
Mortgage insurance denied	2	.00
Other	3,201	8.22
Exempt	1	.00

Source: confidential HMDA, 2018, restricting to approved or denied applications accepted by the GSE automated underwriting systems for conventional, 30-year, purchase or no cash-out refinance, first lien loan applications for one-unit, owner-occupied, single-family non-manufactured houses and excluding high balance loans exceeding the base conforming loan limit and loans a combined loan-to-value ratio exceeding 80%. We also restrict to loans within this sample that report only one denial reason in order to have non-intersecting categories, which includes about 89% of observations.

Figure C.6: Application denials and observable risk: omitting additional denial reasons

This figure presents a binned scatterplot of the denial rate for mortgages accepted by the GSEs' automated underwriting systems on observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1, which is estimated using the MLIS data. The "Baseline" specification omits denials for which any provided denial reason refers to incomplete applications and insufficient cash at closing. Each of the remaining specifications omits the same set (denials due to incomplete applications and insufficient cash at closing) as well as denials due to the reason stated in the line label: debt-to-income (DTI) ratio, employment history, credit history, collateral, unverifiable information, mortgage insurance denied, and other. Source: confidential HMDA, 2018, restricting to approved or denied applications accepted by the GSE automated underwriting systems for conventional, 30-year, purchase or no cash-out refinance, first lien loan applications for one-unit, owner-occupied, single-family non-manufactured houses and excluding high balance loans exceeding the base conforming loan limit and loans a combined loan-to-value ratio exceeding 80%.



D Supplemental material for the model (Sections 4 and 5)

D.1 Surplus

This section compares active and passive intermediation with respect to the total surplus and its components.

We first consider consumer surplus. We focus on the surplus for repaying consumers. For passive intermediation, the consumer surplus is simply $\max(0, \mu - \alpha r_{passive})$. For active intermediation, the consumer surplus for consumers that generate signal z is[44]

$$\pi_C^z = \log\left(1 + n\exp(\mu - \alpha r_{active}^z)\right) + C, \tag{13}$$

where r_{active}^z is the interest rate determined in equation (6) and C is an unknown constant. Due to the unknown constant, we cannot directly comment on the magnitude of the difference between active and passive intermediation. Instead, we focus on how the difference varies with λ_d.

We can also consider the total surplus, which is the sum of lender profits and consumer surplus:

$$S = n\pi_L + (1-\psi)\pi_C^M + \psi\pi_C^L \tag{14}$$

For passive intermediation, the total surplus is simply equal to the consumer surplus since lenders make zero profits:

$$\begin{aligned} S^{passive} &= \max\left(0, \mu - \alpha r_{passive}\right) \\ &= \max\left(0, \mu - \alpha\left(\frac{\rho + \omega\lambda_d}{1-\lambda_d}\right)\right). \end{aligned} \tag{15}$$

For active intermediation, we can compute the total surplus using equations (5) and (13). To compare the total surplus in active and passive intermediation, it is helpful to consider cases where μ is sufficiently large that the consumer surplus in equation (13) can be approximated by $\mu - \alpha r_{active}^z + \log(n) + C$. For more concise notation, let Q^z denote the mass of repaying consumers that produces a given signal z, i.e., $Q^M = 1-\psi$ and $Q^L = \psi$.

[44]See Train (2009) for a reference.

Then we can write

$$
\begin{aligned}
S^{active} &\approx n \sum_z Q^z (1+q)^{1_{\{z=M\}}} \left[s^z \left(r^z_{active}(1-\delta^z) - (\rho + \omega\delta^z) \right) - c(\psi) \right] \\
&\qquad + \sum_z Q^z \left[\mu - \alpha r^z_{active} + \log(n) + C \right] \\
&= \sum_z Q^z \Bigg[n \left(s^z \frac{1}{\alpha(1-s^z)} - c(\psi) \right) \\
&\qquad + \mu - \alpha \left(\frac{\rho + \omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s^z)} \right) + \log(n) + C \Bigg]. \qquad (16)
\end{aligned}
$$

Then the difference can be written as

$$
S^{active} - S^{passive} =
$$

$$
\sum_z Q^z \left[\underbrace{\alpha \left(\frac{\rho + \omega\lambda_d}{1-\lambda_d} - \frac{\rho + \omega\delta^z}{1-\delta^z} \right)}_{\geq 0} + \underbrace{(ns^z - \alpha)\frac{1}{\alpha(1-s^z)}}_{\textbf{sign undetermined}} \underbrace{-nc(\psi)}_{\leq 0} + \underbrace{\log(n)}_{>0} + C \right]. \qquad (17)
$$

The first term represents the benefit of reducing origination costs, which is multiplied by the interest rate sensitivity since this cost is passed on to consumers as higher interest rates. The second term represents the net effect of the markup. Since the markup is a transfer from consumers to lenders, the sign depends on the difference in their marginal values. The third term represents the total screening cost. The fourth term represents the benefits of having multiple differentiated lenders that allow consumers to find a good match corresponding to their idiosyncratic shocks. The final term represents an unknown constant, which we abstract from by focusing on how the difference varies with λ_d.

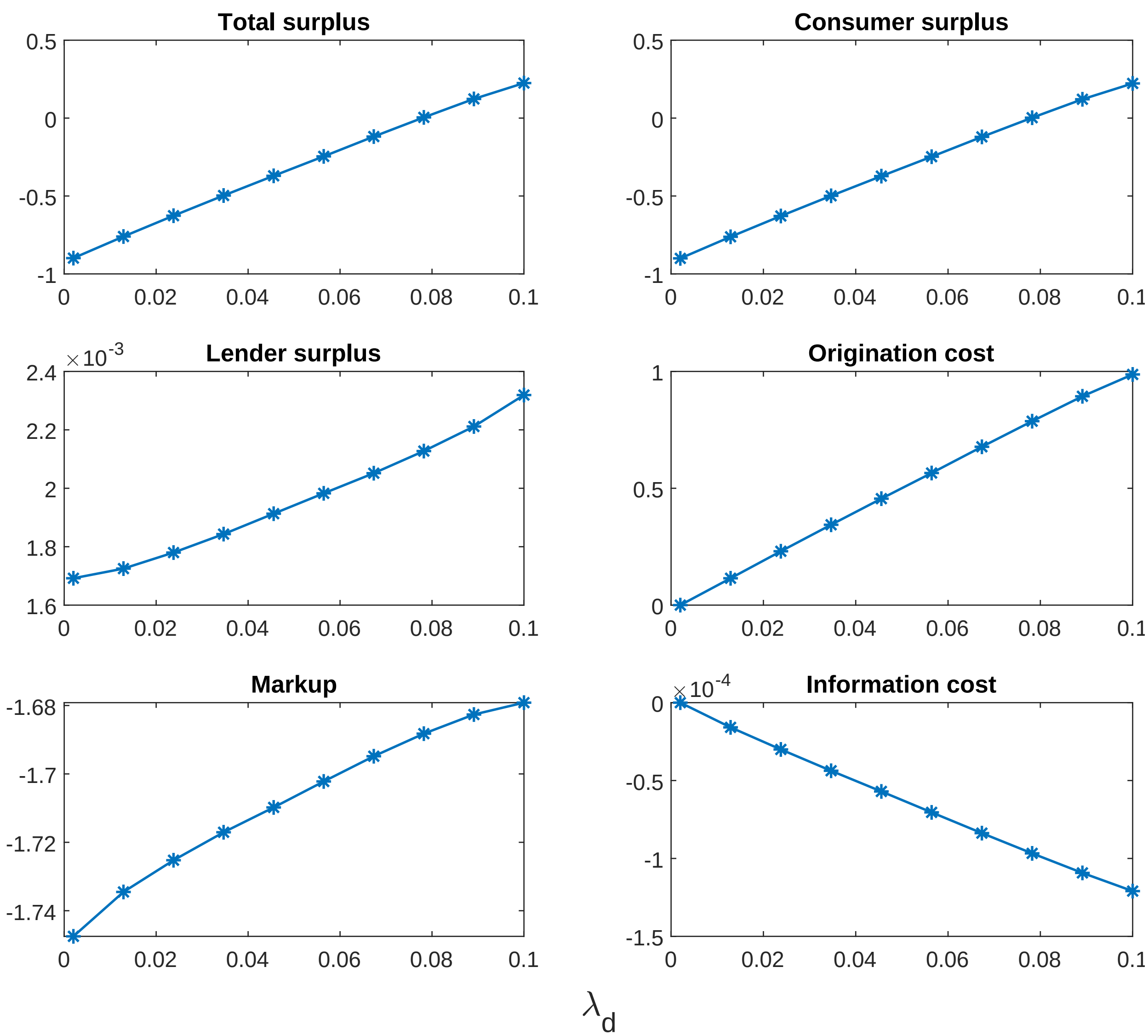
Figure D.1 compares the total surplus generated by active and passive intermediation.[45] Active intermediation generates relatively more surplus for risky consumers, which is primarily driven by the improvement in consumer surplus. Lender surplus also increases with consumer risk since the decreasing interest rate sensitivity allows lenders to charge higher markups, but the magnitude of the increase is smaller. The increase in consumer surplus is driven by the reduction of origination costs, which is a benefit of lender screening. Markups, which represent a transfer from consumers to lenders, reduce the total surplus since consumers have a marginal value of α, which is at least 5 for all levels of λ_d,

[45] Note that the constant C in equation (13) is assumed to be zero for the purpose of generating this figure. The magnitude of the difference for the total surplus and consumer surplus is only determined up to a constant, so we instead focus on how the difference varies with λ_d.

whereas the marginal value for lenders is $ns^z \leq 1$. Markups become slightly less inefficient as λ_d increases since the interest rate sensitivity is decreasing. Finally, total information costs increase with λ_d, but the magnitude is relatively small.

Figure D.1: Surplus decomposition

These figures show active minus passive intermediation for the following: total surplus, consumer surplus, lender surplus, origination cost, markup, and information cost. The origination cost and markup components are correspond to the first and second underlined terms in equation (17), respectively. Note that the constant C in equation (13) is assumed to be zero for the purpose of generating this figure. The magnitude of the difference for the total surplus and consumer surplus is only determined up to a constant. See Table 6 for parameters.



D.2 Other supplementary material for the model

Figure D.2: Active intermediation as ω varies

These figures show various features of the model for a low loss given default ω and a high loss given default. The *denial rate* is the probability that a consumer's loan application is rejected. The *default rate* is the fraction of approved applications that consist of defaulting consumers. The *interest rate* for active intermediation is decomposed as the *origination cost* (which is the zero-profits interest rate), the *information cost* (which is the cost associated with the information level ψ), and the *markup*. See Table 6 for parameters.

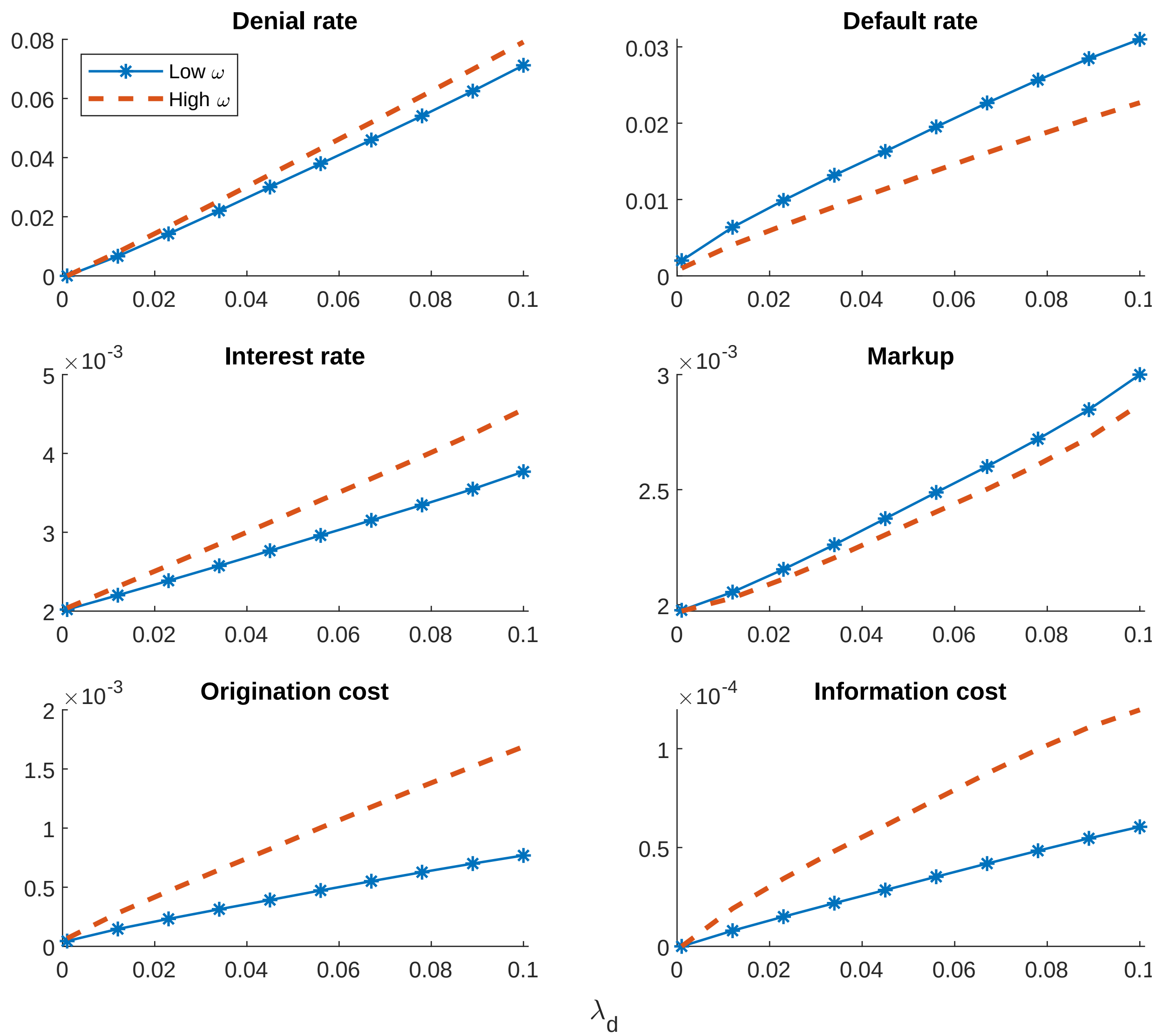
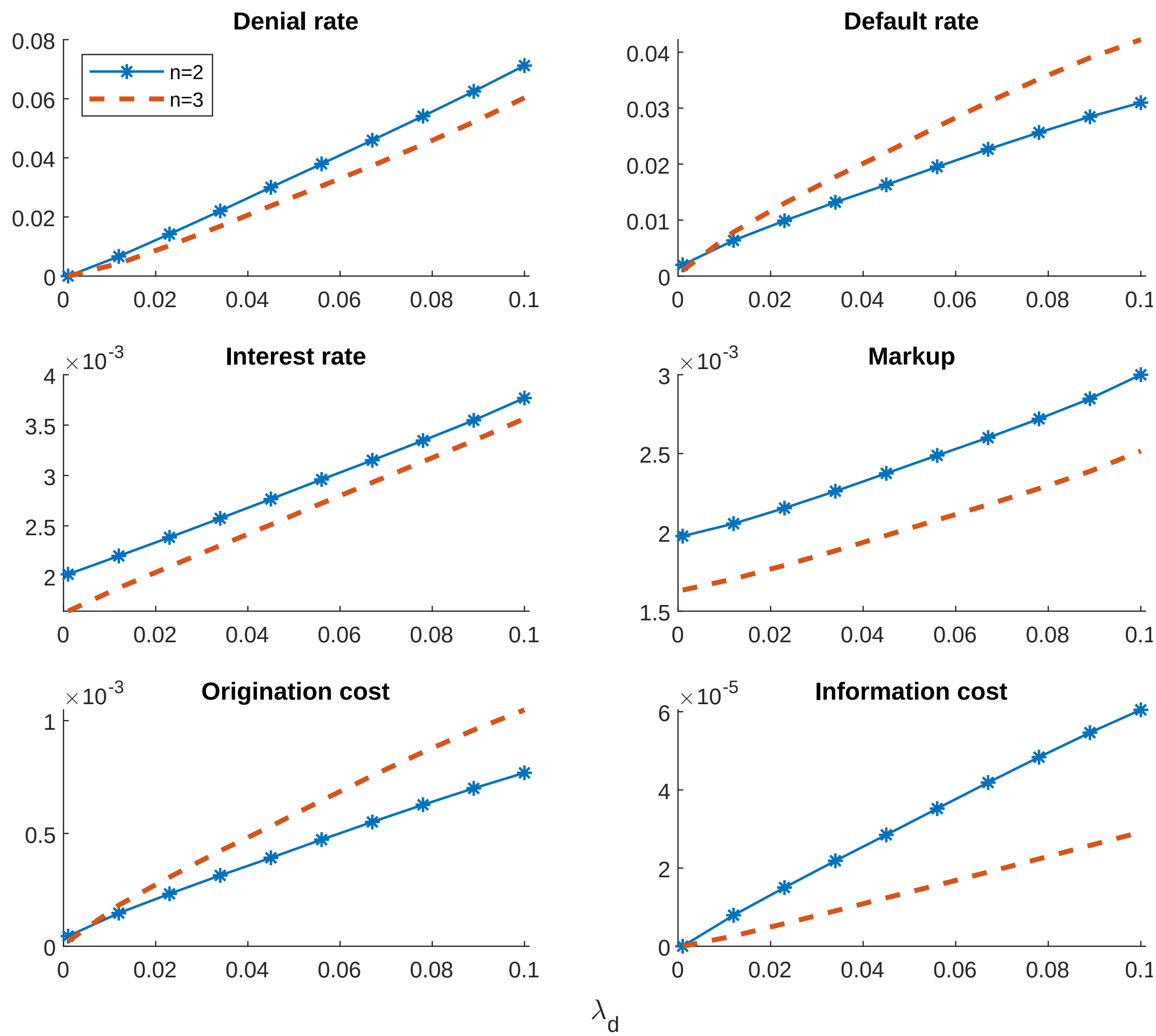


Figure D.3: Active intermediation as n varies

These figures show various features of the model when the number of lenders n is equal to 2 or 3. The *denial rate* is the probability that a consumer's loan application is rejected. The *default rate* is the fraction of approved applications that consist of defaulting consumers. The *interest rate* for active intermediation is decomposed as the *origination cost* (which is the zero-profits interest rate), the *information cost* (which is the cost associated with the information level ψ), and the *markup*. See Table 6 for parameters.

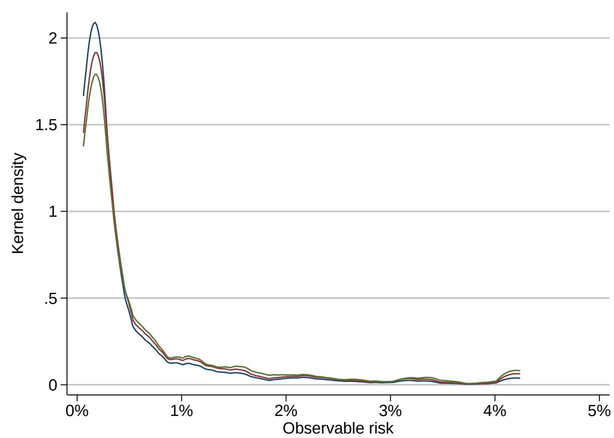


E Supplemental material for the analysis of heterogeneous lenders (Section 6)

Figure E.1: Distributions of observable risk

These figures present the distribution of observable risk for banks, nonbank-nonfintechs, and fintechs. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Figure E.1a shows the kernel density, which is computed using the Epanechnikov kernel with a bandwidth of 0.1. Figure E.1b shows the cumulative distribution function. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

(a) Density



(b) Cumulative distribution function

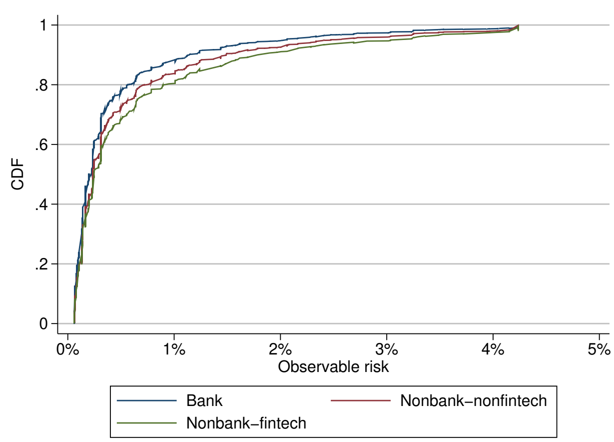
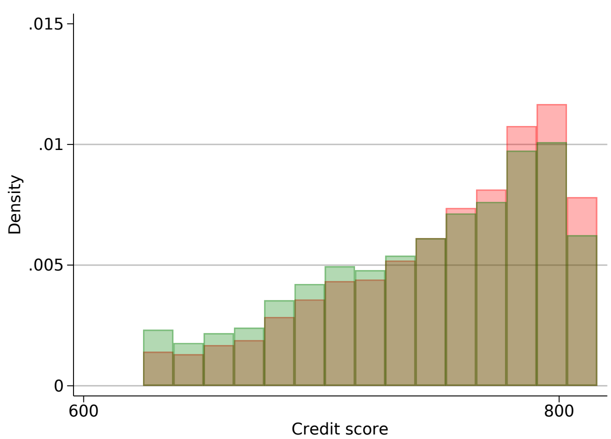


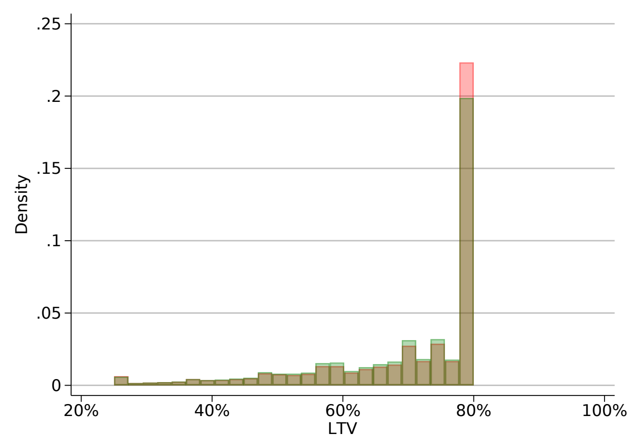
Figure E.2: Distributions of risk characteristics

These figure present the distribution of credit score, the loan-to-value ratio, the debt-to-income ratio, and observable risk for loans originated by banks and nonbanks. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

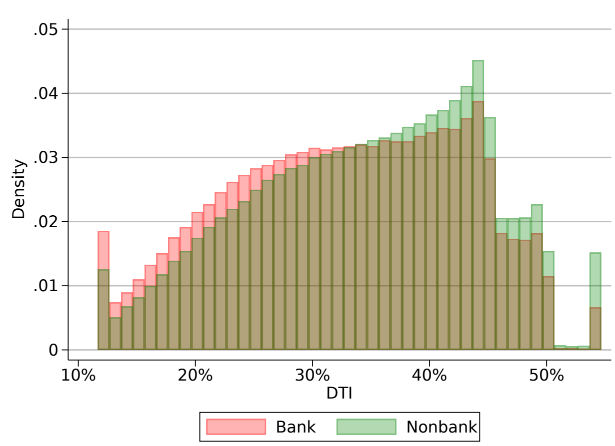
(a) Credit score



(b) Loan-to-value ratio



(c) Debt-to-income



(d) Observable risk

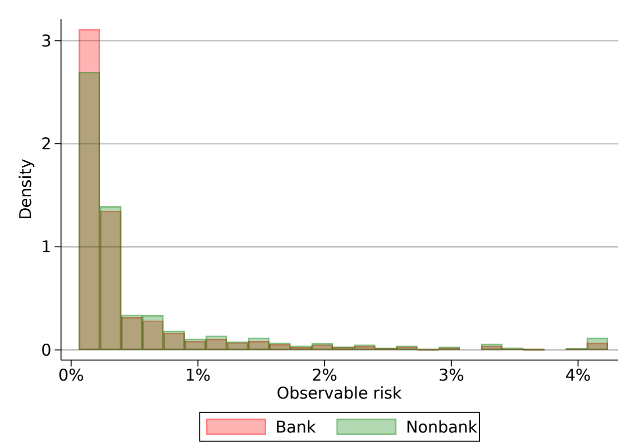


Table E.1: Observable risk and lender type

(a) Banks

	Mean	P10	P25	P50	P75	P90
Observable risk	0.45	0.07	0.10	0.20	0.42	1.11
Credit score	752.56	683.00	722.00	764.00	790.00	803.00
LTV	70.30	50.00	64.00	77.00	80.00	80.00
DTI	32.87	19.09	25.25	33.42	41.05	45.17

(b) Nonbank-nonfintechs

	Mean	P10	P25	P50	P75	P90
Observable risk	0.55	0.07	0.12	0.25	0.58	1.38
Credit score	745.79	673.00	711.00	756.00	787.00	801.00
LTV	69.61	49.00	63.00	75.00	80.00	80.00
DTI	34.46	20.62	27.15	35.39	42.40	46.40

(c) Fintechs

	Mean	P10	P25	P50	P75	P90
Observable risk	0.63	0.07	0.12	0.25	0.68	1.81
Credit score	740.79	663.00	702.00	750.00	786.00	802.00
LTV	68.53	49.00	61.00	73.00	80.00	80.00
DTI	34.32	20.44	26.87	35.01	42.34	46.90

Note: These tables present summary statistics for observable risk characteristics (credit score, loan-to-value ratio (%), debt-to-income ratio (%), and observable risk) for banks, nonbank-nonfintechs, and fintechs. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table E.2: Origination revenue, observable risk, and lender type

	(1) Orig. rev.	(2) Orig. rev.	(3) Closing costs	(4) Closing costs	(5) Second. income	(6) Second. income
Observable risk	0.473***	0.445***	0.092***	0.068***	0.383***	0.377***
	(97.17)	(64.87)	(34.61)	(19.60)	(79.70)	(56.48)
Nonbank	0.569***	0.536***	0.189***	0.160***	0.386***	0.380***
	(71.93)	(57.16)	(44.89)	(32.29)	(49.76)	(41.33)
Observable risk $\times$ Nonbank		0.056***		0.048***		0.011
		(5.78)		(9.26)		(1.12)
Observations	162,561	162,561	162,561	162,561	162,561	162,561
R^2	0.547	0.547	0.362	0.362	0.440	0.440
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Column (1) regresses origination revenue on observable risk and an indicator for nonbanks while controlling for ZIP code by year-quarter fixed effects and adding the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Column (2) is similar except including the interaction of observable risk and the nonbank indicator. Columns (3) and (4) are analogous except that the dependent variable is closing costs as a percentage of the loan amount. Columns (5) and (6) are analogous except that the dependent variable is secondary marketing income. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac) merged with HMDA, 2018, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Table E.3: Empirical comparison of banks and nonbanks: distinguish by fintech

(a) Bank vs nonbank-nonfintech

	(1) Nonbank	(2) IR-gfee	(3) IR-gfee	(4) Default	(5) Default
Observable risk	3.397***	0.050***	0.045***	0.956***	0.806***
	(44.56)	(132.25)	(91.29)	(40.11)	(27.56)
Nonbank-nonfintech		0.041***	0.036***	0.178***	0.011
		(78.16)	(58.42)	(9.87)	(0.54)
Observable risk × Nonbank-nonfintech			0.010***		0.327***
			(13.55)		(6.78)
Observations	817,649	817,649	817,649	817,649	817,649
R^2	0.187	0.656	0.656	0.157	0.158
ZIP × Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

(b) Bank vs nonbank-fintech

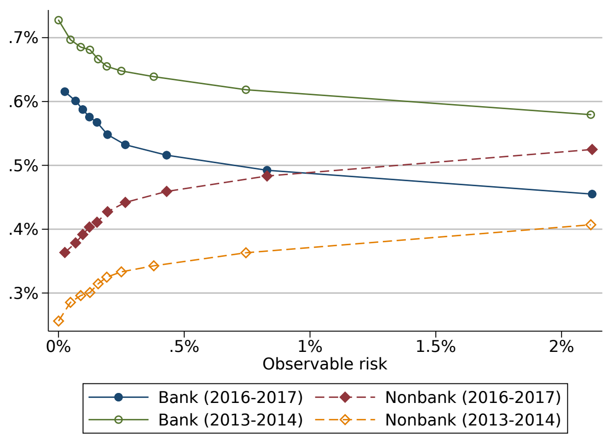
	(1) Nonbank	(2) IR-gfee	(3) IR-gfee	(4) Default	(5) Default
Observable risk	2.422***	0.042***	0.046***	0.817***	0.809***
	(34.53)	(88.55)	(89.76)	(29.90)	(27.42)
Nonbank-fintech		0.077***	0.092***	0.150***	0.119***
		(69.49)	(69.82)	(3.88)	(2.76)
Observable risk × Nonbank-fintech			-0.025***		0.051
			(-19.09)		(0.66)
Observations	553,534	553,534	553,534	553,534	553,534
R^2	0.184	0.674	0.674	0.193	0.193
ZIP × Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: In Table E.3a, the sample includes banks and nonbank-nonfintechs. Column (1) regresses an indicator for a nonbank-nonfintech (multiplied by 100) on observable risk while controlling for ZIP code by year-quarter fixed effects and the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Column (2) is analogous except that the dependent variable is the interest rate net of g-fees and we add the nonbank-nonfintech indicator. Column (3) is similar to column (2) except adding the interaction between the nonbank indicator and observable risk. Columns (4) and (5) are analogous to (2) and (3) except that the dependent variable is an indicator for default (multiplied by 100). Table E.3b is analogous except replacing nonbank-nonfintechs with nonbank-fintechs. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

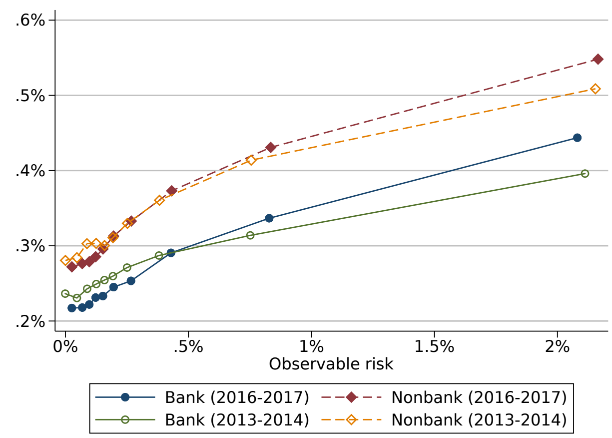
Figure E.3: Empirical comparison of banks and nonbanks over time

Figure 7a presents a binned scatterplot of dummy variables indicating whether a loan was sold to the GSEs by a bank or a nonbank on observable risk (computed based on the sample from 2013 to 2017) while controlling for origination year-month fixed effects. We show this relationship for observations in 2016-2017 and for 2013-2014. Figure 7b presents a binned scatterplot of the spread of the interest rate net of the total g-fee relative to the best available rate on observable risk while controlling for origination year-month fixed effects and splitting by bank versus nonbank sellers and 2013-2014 versus 2016-2017. The best available rate is determined by computing the 10th percentile of the interest rate net of the total g-fee for the borrowers in the lowest quartile of observable risk in each week. Figure 7c presents a binned scatterplot of default (multiplied by 100) on the interest rate net of the total g-fee while controlling for origination year-month fixed effects and observable risk and splitting by bank versus nonbank sellers and 2013-2014 versus 2016-2017. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2013-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%. Note that we relax the sample restriction of requiring the upfront g-fee to be within 25 basis points of the value of the first table of the g-fee matrix since the precise data on g-fees is not consistently available before 2016.

(a) Market share and observable risk



(b) Interest rates and observable risk



(c) Default and observable risk

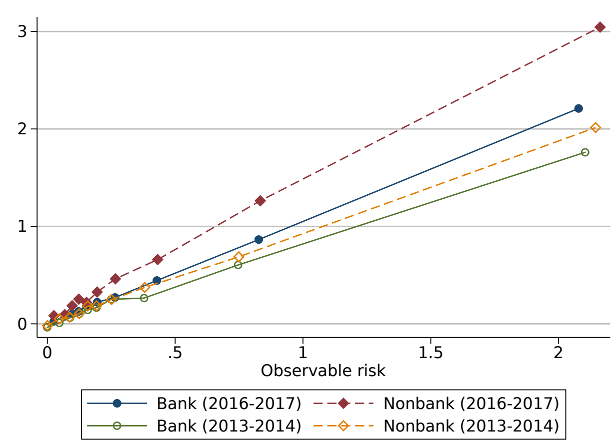


Table E.4: Market share and observable risk over time

	(1) Nonbank	(2) Nonbank	(3) Nonbank	(4) Nonbank	(5) Nonbank
Observable risk	3.471***	6.664***	7.353***	5.931***	5.518***
	(36.64)	(58.54)	(68.45)	(57.39)	(50.78)
Observations	618,139	375,635	480,799	564,630	445,854
R^2	0.140	0.185	0.168	0.158	0.167
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Year	2013	2014	2015	2016	2017

Note: Each column regresses an indicator for nonbank (multiplied by 100) on observable risk while controlling for ZIP code by year-quarter fixed effects for a particular year. We estimate observable risk based on the sample in each year. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2013-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%. Note that we relax the sample restriction of requiring the upfront g-fee to be within 25 basis points of the value of the first table of the g-fee matrix since the precise data on g-fees is not consistently available before 2016.

Table E.5: Interest rates, observable risk, and lender type over time

	(1) IR-gfee	(2) IR-gfee	(3) IR-gfee	(4) IR-gfee	(5) IR-gfee
Observable risk	0.074***	0.068***	0.073***	0.100***	0.094***
	(111.55)	(115.23)	(107.90)	(154.98)	(148.83)
Nonbank	0.059***	0.073***	0.064***	0.075***	0.062***
	(68.06)	(89.89)	(20.91)	(104.51)	(69.52)
Observations	610,831	373,055	477,033	561,486	445,162
R^2	0.668	0.433	0.054	0.390	0.230
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Year	2013	2014	2015	2016	2017

Note: Each column regresses the interest rate net of g-fees on an indicator for nonbanks and observable risk while controlling for ZIP code by year-quarter fixed effects for a particular year. T-statistics computed using robust standard errors are reported in parentheses. Note that we relax the sample restriction of requiring the upfront g-fee to be within 25 basis points of the value of the first table of the g-fee matrix since the precise data on g-fees is not consistently available before 2016. We also estimate observable risk based on the sample in each year rather than applying the model estimated on 2016-2017. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2011-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%.

Table E.6: Default, observable risk, and lender type over time

	(1) Default	(2) Default	(3) Default	(4) Default	(5) Default
Observable risk	0.812***	0.857***	0.932***	1.127***	1.206***
	(30.22)	(28.01)	(30.67)	(34.76)	(34.90)
Nonbank	0.072***	0.082***	0.107***	0.160***	0.194***
	(4.11)	(3.35)	(5.23)	(7.64)	(7.45)
Observations	618,139	375,635	480,799	564,630	445,854
R^2	0.130	0.163	0.143	0.141	0.147
ZIP $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Year	2013	2014	2015	2016	2017

Note: Each column regresses an indicator for default (multiplied by 100) on an indicator for nonbanks and observable risk while controlling for ZIP code by year-quarter fixed effects for a particular year. T-statistics computed using robust standard errors are reported in parentheses. Note that we relax the sample restriction of requiring the upfront g-fee to be within 25 basis points of the value of the first table of the g-fee matrix since the precise data on g-fees is not consistently available before 2016. We also estimate observable risk based on the sample in each year rather than applying the model estimated on 2016-2017. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2011-2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%.

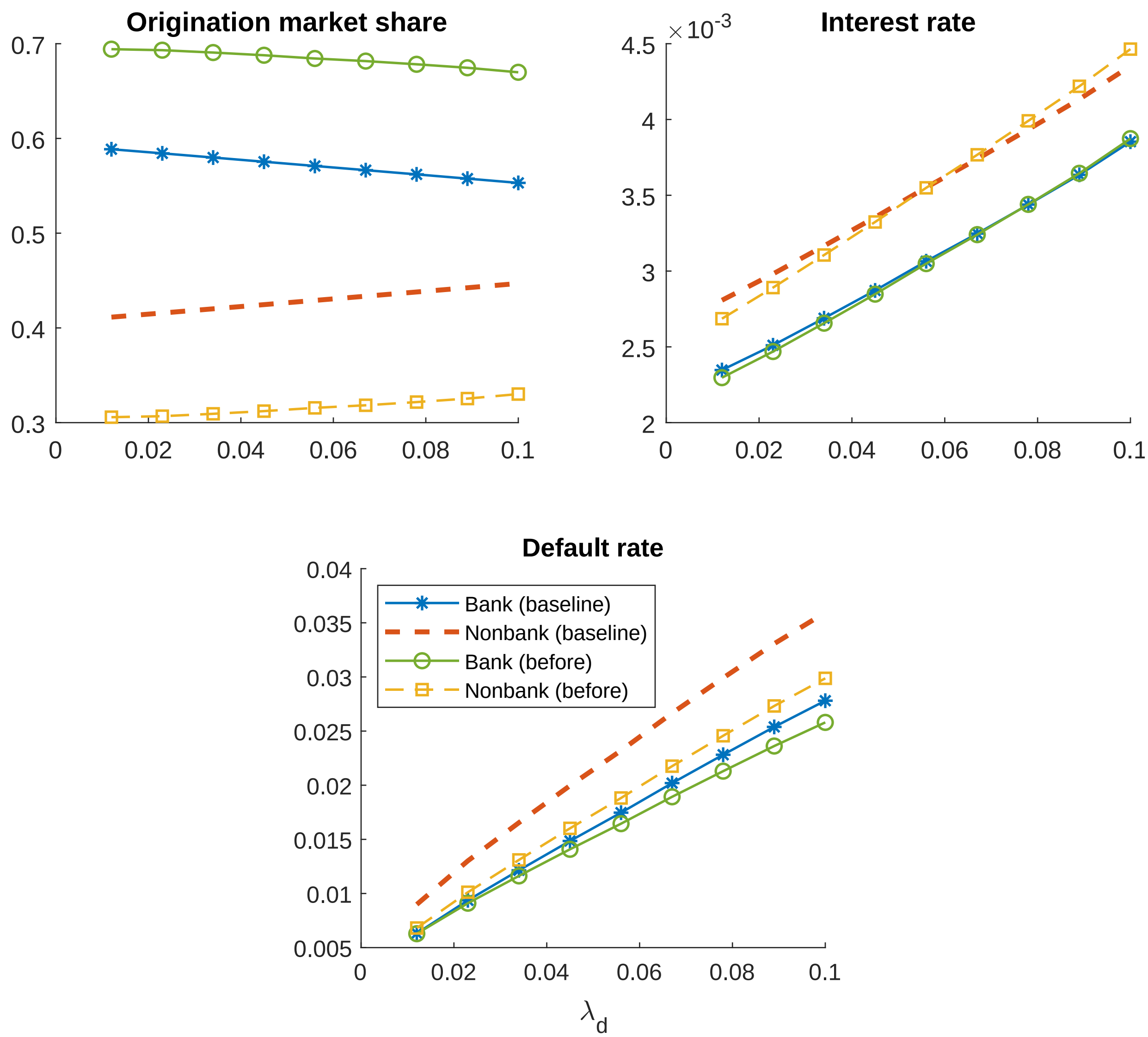
Table E.7: Nonbanks, borrower self-assessed risk, and borrower satisfaction

	(1) Risk index	(2) Risk index	(3) Risk index	(4) Satisfaction index	(5) Satisfaction index	(6) Satisfaction index
Observable risk	0.253***	0.274***	0.227***	-0.051	-0.118*	-0.045
	(3.73)	(3.70)	(2.79)	(-0.88)	(-1.88)	(-0.55)
Nonbank	0.112**			-0.003		
	(2.12)			(-0.07)		
Nonbank-nonfintech		0.095*			-0.066	
		(1.72)			(-1.28)	
Nonbank-fintech			0.276**			0.343***
			(2.43)			(3.67)
Observations	2,048	1,909	1,232	2,048	1,909	1,232
R^2	0.281	0.287	0.331	0.226	0.239	0.312
State x Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Columns (1) through (3) regress an index of borrower self-assessed risk on observable risk and an indicator for nonbanks, nonbank-nonfintechs (while excluding nonbank-fintechs), and nonbank-fintechs (while excluding nonbank-nonfintechs), respectively, while controlling for state by year-quarter fixed effects. The self-assessed risk index assigns a score of 1, 2, or 3 for being "not at all", "somewhat", or "very", respectively, concerned about qualifying for a mortgage and when rating the likelihood of having difficulties meeting mortgage payments, experiencing a layoff or other reduction in employment, or some other personal financial crisis; it also assigns a score of 1, 2, 3, for being "very", "somewhat", or "not at all", respectively, when rating the likelihood of, upon experiencing an unexpected personal financial crisis, being able to pay bills for the next 3 months without borrowing, getting significant help from family or friends, borrowing a significant amount from a bank or credit union, and significantly increasing income. The index is computed by summing the scores and then normalizing the resulting distribution to have a mean of 0 and standard deviation of 1. Columns (4) through (6) are analogous except that the dependent variable is an index of borrower satisfaction with the lender. The lender satisfaction index assigns a score of 1, 2, or 3 for being "not at all", "somewhat", or "very", respectively, satisfied with the lender/mortgage broker, the application process, the documentation process, the loan closing process, the information in the mortgage disclosure documents, the timeliness of the mortgage disclosure documents, and the settlement agent; it then sums the scores and normalizes the resulting distribution to have a mean of 0 and a standard deviation of 1. Source: National Survey of Mortgage Originations merged with Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2013-2017, restricting to GSE-acquired, fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, site-built properties and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, and loans with a loan-to-value ratio exceeding 80%.

Figure E.4: Model emulation of change over time for banks and nonbanks

These figures show various features of the version of the model with a bank lender and a nonbank lender at two periods of time. In the "baseline" case, the nonbank lender has higher funding costs ρ and lower loss given default ω. In the before case, the nonbank lender is relatively less favored by consumers and has relatively higher funding costs and losses given default. The *origination market share* refers to the share of originated loans associated with a particular lender. The *interest rate* (IR) is the signal-weighted average interest rate, as described further in Section 4.3. The *default rate* is the fraction of approved applications that consist of defaulting consumers.



F Alternative model with strategic interaction

This section show that the results from the model are qualitatively robust to an alternative model in which lenders draw different signals about a consumer's default risk and strategically bid the interest rate. Specifically, the alternative model also shows that lender overlays are most harmful to low-to-medium risk consumers compared to a counterfactual in which the discretionary behavior of lenders is eliminated. The alternative model also shows that the empirical differences between banks and nonbanks are more consistent with nonbanks having a lower loss given default rather than differences in screening quality.

F.1 Agents

There are two types of agents: consumers and lenders. All agents are risk neutral.

A consumer can either buy a house requiring 1 unit of external capital or take an outside option whose value is normalized to zero. Consumers are willing to pay up to A in financing costs. There are two quality types θ of consumers: type d consumers default, while type r consumers repay the loan.[46] Lenders cannot perceive the type of an individual consumer, but they know the frequencies of the two types in the population, $\lambda_d \leq \frac{1}{2}$ and $\lambda_r = 1 - \lambda_d$.

F.2 Timeline overview

In period $t = 0$, lenders invest in underwriting technology, which could involve improving their risk assessment models, investing labor hours in careful loan processing, and potentially also collecting additional information about applicants beyond what is required for the GSEs' underwriting criteria.

In period $t = 1$, a consumer applies for a loan with a set of lenders. To focus on the discretionary behavior of lenders as distinct from the underwriting processes of the GSEs, we specifically consider a loan that satisfies the GSEs' underwriting criteria. The lenders first estimate the consumer's default risk, which is represented by allowing each lender to independently draw a signal whose informativeness depends on the quality of its screening technology. Then, lenders that perceive the consumer as too risky reject the consumer's application, while the remaining lenders compete with each other.

In period $t = 2$, the consumer receives the outside option payoff of zero if it did not obtain funding, otherwise, it either repays the loan or defaults.

[46] For simplicity, we abstract from prepayment risk, which is more pertinent in the context of servicing. We focus instead on a lender's losses from originating mortgages that default, such as repurchases or other penalties imposed by the GSEs. In particular, prepayments could be included in the set of repaid loans.

An elaboration of the model follows in approximately backward order.

F.3 Risk estimates

This section shows how lenders estimate the default risk of a consumer, which can be described in two parts. First, each lender draws a signal from a distribution that depends on the quality of its underwriting and the quality of the consumer. Second, a lender then adjusts this estimate to take into account the additional information that it would learn conditional on being chosen by the consumer.

F.3.1 Risk estimate conditional on a lender's own signal

Consider a consumer that applies for a loan with n lenders. Suppose that each lender i has some information about the consumer, which is represented by the information level $\psi_i \in [0, 2\lambda_d]$ that summarizes the quality of the screening process.[47] For simplicity, we focus on a symmetric equilibrium in which all lenders have the same information level ψ. See Internet Appendix H for a version of the model where lenders can have different information levels.

At the beginning of the loan application phase, each lender independently draws a privately observed signal $s_i \in [0, 1]$ that depends on the consumer's quality type and the information level of the lenders according to the pdf

$$f(s|d;\psi) = \left(1 + \left(\frac{1}{2} - s\right)\frac{\psi}{\lambda_d}\right) \tag{F.1}$$

$$f(s|r;\psi) = \left(1 + \left(s - \frac{1}{2}\right)\frac{\psi}{\lambda_r}\right) \tag{F.2}$$

The information level corresponds to the precision of the signal. For example, if $\psi = 0$ then both types produce a uniformly distributed signal, whereas the signal distributions become more differentiated, and the signal therefore becomes more informative, as ψ increases.

The posterior risk of default conditional on receiving signal s with information ψ can be expressed as

$$\begin{aligned} D(s;\psi) &\equiv Pr(d|s;\psi) \\ &= \lambda_d + \left(\frac{1}{2} - s\right)\psi \end{aligned} \tag{F.3}$$

[47] Note that the information level is bounded to ensure that the signal distributions described in (F.1) and (F.2) are nonnegative.

The properties of the posterior risk are represented graphically in Figure I.1. The posterior risk is decreasing in the signal and equal to the prior λ_d at the threshold point $s = \frac{1}{2}$. The strength of a signal in shifting the prior is increasing in its distance from this threshold as well as the information level.

F.3.2 Adjustment of risk estimate conditional on supplying the loan

Conditional on the signals, competition among the lenders is formally represented as a *second-price sealed-bid auction* where the bids correspond to interest rate offers.[48] Note that the supplying lender, or the lender with the most competitive offer, can make an inference about the signal of the next most competitive lender based on the equilibrium outcome, resulting in an adjustment of its estimated posterior risk of default.[49] By a general result for common value auctions from Milgrom (1981), there is a symmetric equilibrium in which each lender's interest rate offer is based on the minimum posterior risk of default that it could have conditional on supplying the loan and updating its posterior risk based on the equilibrium outcome.[50] Conditioning on winning the auction accounts for the "winner's curse", or the tendency for the winner of a common value auction to have an over-optimistic assessment.

Denote the jth order statistic of k signal draws by $s_{j:k}$. To capture the additional information acquired after observing the equilibrium outcome, it is helpful to consider the posterior risk conditional on the lender's own signal s and inferring from the equilibrium interest rate the signal of the next most competitive lender t:[51]

$$\begin{aligned} D(s,t;\psi,n) &\equiv Pr(d|s_{n:n} = s, s_{n-1:n} = t; \psi, n) \\ &\underset{\psi\approx 0}{\approx} \lambda_d + \frac{1}{2}(n - 2s - nt)\psi \end{aligned} \tag{F.4}$$

The *minimum* posterior risk conditional on winning with signal s occurs when the

[48]The auction is analogous to Bertrand competition except that the perceived costs of producing loans are based on estimates of a common cost based on the consumer's quality. For simplicity, the auction is assumed to be sealed-bid so that the condition of winning the auction and the equilibrium interest rate are the only sources of information about the signals of the other lenders. The assumption that banks cannot observe each other's offers is similar to other models of bank competition with screening, such as Broecker (1990), Cao and Shi (2001), and Ruckes (2004).

[49]Note that the supplying lender can infer the signal of the next most competitive lender exactly if any other lender makes an offer, as it will be reflected in the equilibrium interest rate. If no other lenders make an offer, then the supplying lender can only infer that all the other lenders received a small enough signal to discourage lending.

[50]See Internet Appendix I.2 for a proof in this environment.

[51]See Internet Appendix I.3 for a calculation. The notation $\underset{\psi\approx 0}{\approx}$ indicates that the expression is a first order approximation around $\psi = 0$.

next most competitive lender has the same posterior risk,[52] which can be expressed as

$$D(s, s; \psi, n) = \lambda_d + \frac{1}{2}(n - (n+2)s)\psi \tag{F.5}$$

The minimum posterior risk conditional on winning the auction qualitatively inherits some of the properties of the posterior risk conditional on just the signal, $D(s; \psi)$. Specifically, the minimum posterior risk is decreasing in the signal, and information increases the strength of the signal.

F.4 Interest rate offers

A lender that is willing to lend to the consumer participates in the auction by offering an interest rate R. Again, to focus on the decisions of lenders as distinct from the GSEs, we assume that the interest rate is net of g-fees. Suppose that the cost of funding is equal to ρ. If the loan defaults, then the lender incurs an expected loss given default of $\omega \geq 0$ due to, for example, repurchase risk (Goodman (2017)). A lender's expected profits upon winning the auction can therefore be expressed as

$$(1+R) - \omega D - (1+\rho) = R - (\omega D + \rho) \tag{F.6}$$

The zero-profits interest rate can be written as a markup over the cost of funds that corresponds to the risk

$$\underline{R}(D) = \omega D + \rho \tag{F.7}$$

A lender's interest rate offer is equal to the zero-profits interest rate corresponding to the minimum posterior risk conditional on being chosen by the consumer (see equation (F.5)).[53]

Proposition F.1. *A lender's interest rate offer is equal to*

$$\underline{R}(D(s, s; \psi, n)) = \omega \left[\lambda_d + \frac{1}{2}(n - (n+2)s)\psi\right] + \rho \tag{F.8}$$

If only one lender has a sufficiently optimistic signal to offer a loan, then it fully ap-

[52] This is because a lender wins only if it has a lower posterior risk. Hence, the information contained in the other lender's action can only lead the supplying lender to increase its posterior risk estimate. This adjustment is relatively small when the next most competitive lender has a similar estimate of the consumers' default risk and vanishes in the limiting case where the estimated default risk of the two lenders is the same.

[53] See Internet Appendix I.2 for a proof. Note that, as shown in the proof, a lender making this offer always obtains a nonnegative expected payoff upon supplying the loan.

propriates any potential surplus by charging an interest rate that is equal to the consumer's willingness to pay, A. This formal convention is consistent with the motivating intuition that a consumer's bargaining power derives from leveraging competing offers from other informed lenders.[54]

F.5 Participation decision

A lender offers a loan on the condition that its expected profits after learning about the action of the next most competitive lender from the equilibrium outcome will be non-negative. Consider a symmetric equilibrium in which there exists a threshold $\underline{s}$ such that a lender makes an offer when $s \geq \underline{s}$.[55,56]

Proposition F.2. *A lender's participation threshold is equal to*

$$\underline{s} = \frac{n}{n+1} + \frac{2(\omega\lambda_d + \rho - A)}{(n+1)\omega\psi} \tag{F.9}$$

Lenders make all of their decisions, including whether to participate and any interest rate offer, simultaneously.

F.6 Equilibrium summary

The resolution of the auction is summarized as follows. If more than one lender is willing to lend, then the lenders offer $\underline{R}(D(s_i, s_i; \psi, n))$ and the lender with the lowest offer supplies the loan at the second lowest offer, $\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n))$. If only one lender is willing to lend, then it charges the maximum possible interest rate A. If no lender obtains a sufficiently optimistic assessment to be willing to offer credit (i.e., $s_i < \underline{s}$ for each lender i), then the consumer takes the outside option.

Note that a few key properties of the model are as follows:

1. The *probability of receiving credit* (averaged over both types of consumers) is given by

$$\lambda_d Pr(s_{n:n} > \underline{s}|d;\psi) + \lambda_r Pr(s_{n:n} > \underline{s}|r;\psi). \tag{F.10}$$

[54]Note that the resolution of the equilibrium in the case where only one lender is willing to lend is a modeling choice since the second-price auction is not defined.

[55]See Internet Appendix I.4 for a calculation.

[56]Note that $\underline{s}_i$ need not occur in the support of the signal, $[0, 1]$, but the conclusion is still the same. That is, if $\underline{s}_i \leq 0$ then the lender always makes an offer, and if $\underline{s}_i \geq 1$ then the lender never makes an offer.

2. The *default rate* is the fraction of consumers receiving credit that default:

$$\frac{\lambda_d Pr(s_{n:n} > \underline{s}|d;\psi)}{\lambda_d Pr(s_{n:n} > \underline{s}|d;\psi) + \lambda_r Pr(s_{n:n} > \underline{s}|r;\psi)}. \tag{F.11}$$

3. The *expected interest rate* (averaged over both types of consumers) is given by:

$$\begin{aligned} R_{exp} = \lambda_d E_{s_{n-1:n}} &\left[\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) 1_{\{s_{n-1:n} \geq \underline{s}\}} | d; \psi \right] \\ &+ \lambda_r E_{s_{n-1:n}} \left[\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) 1_{\{s_{n-1:n} \geq \underline{s}\}} | r; \psi \right]. \end{aligned} \tag{F.12}$$

F.7 A lender's information acquisition decision

Lenders can acquire information $\eta \geq 0$ with a convex acquisition cost $\mu\frac{\eta^2}{2}$, which could represent lenders developing more sophisticated risk assessment models or investing labor hours in careful loan processing. In general, we can also allow for there to be information that is relatively costless to process $z \geq 0$, in which case the total information level is the sum $\psi = z + \eta$. However, we focus on the case where z is equal to 0.

The value of information to a lender consists in efficiently providing credit to applicants that are likely to repay as well as undercutting competitors with noisier signals. For simplicity, consider a symmetric equilibrium in which all lenders commit to acquire the same information level. In particular, lenders choose the level of information $\psi \in [0, 2\lambda_d]$ to maximize their total expected profits

$$\begin{aligned} \pi_L = &E_{s, s_{n-1:n}} \left[\underbrace{(A - \underline{R}(D(s, s_{n-1:n}; \psi, n)))}_{=R-\underline{R} \text{ as in (F.6), with no competing lenders}} 1_{\{s = s_{n:n} \geq \underline{s}, s_{n-1:n} \leq \underline{s}\}} \right] \\ &+ E_{s, s_{n-1:n}} \left[\underbrace{(\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) - \underline{R}(D(s, s_{n-1:n}; \psi, n)))}_{=R-\underline{R} \text{ as in (F.6), with competing lenders}} 1_{\{s = s_{n:n} \geq \underline{s}, s_{n-1:n} \geq \underline{s}\}} \right] \\ &- \mu \frac{(\psi - z)^2}{2}, \end{aligned} \tag{F.13}$$

where the expectation averages over cases where the lender wins the auction and obtains a profit corresponding to the difference between the interest rate that it collects and its zero-profits interest rate.[57]

[57] See Internet Appendix I.5 for a calculation lender profits.

G Counterfactual: active vs. passive intermediation in the alternative model

This section shows that, compared to a counterfactual in which the discretionary behavior of lenders is eliminated, lender overlays lead to relatively lower interest rates borrowers with greater observable risk.

G.1 Definitions

The definitions are analogous to the baseline model (Section 5.1). We define *active intermediation* as the system described in the model. We define *passive intermediation* as a system in which there is no additional screening for an application that has satisfied the GSEs' underwriting criteria. In particular, all applications that are accepted by the GSEs' underwriting criteria are offered a loan, and the interest rate for a given level of observable risk is determined by a simple zero-profits condition.[58] We can summarize some key properties of passive intermediation as follows:

1. Interest rate $= \underline{R}(\lambda_d) = \rho + \omega\lambda_d$
2. Probability of receiving credit $= 1$ if $\underline{R}(\lambda_d) \leq A$ or 0 if $\underline{R}(\lambda_d) > A$ since the interest rate exceeds the consumer's willingness to pay
3. Default rate $= \lambda_d$

We focus on which system results in a lower average interest rate. Under active intermediation, the interest rate can be decomposed into 3 components: the ex-ante *information cost*, an *origination cost* that corresponds to the zero-profits interest rate $\underline{R}(D) = \rho + \omega D$, and a residual *markup* that corresponds to a lender's total expected profits. In particular, if the expected equilibrium interest payment under active intermediation is R_{exp}, then the

[58] Note that passive intermediation yields the same result as a market with perfect competition.

components can be written as follows:

$$
\begin{aligned}
R_{exp} = \quad & \underbrace{n\mu\frac{(\psi - z)^2}{2}}_{\text{total information cost}} \\
& + \underbrace{E_{s_{n:n}, s_{n-1:n}}[\underline{R}(D(s_{n:n}, s_{n-1:n}; \psi, n))]}_{\text{origination cost}} \\
& + \underbrace{R_{exp} - \left(n\mu\frac{(\psi - z)^2}{2} + E_{s_{n:n}, s_{n-1:n}}[\underline{R}(D(s_{n:n}, s_{n-1:n}; \psi, n))]\right)}_{\text{markup}}
\end{aligned}
\tag{G.14}
$$

On the one hand, active intermediaries may exhibit lower origination costs since they lend to consumers that are more likely to repay. On the other hand, active intermediaries also have information acquisition costs and an opportunity to charge a markup, i.e.,

$$
\begin{aligned}
R_{exp} - \underline{R}(\lambda_d) = & \underbrace{\text{origination cost} - \underline{R}(\lambda_d)}_{\leq 0} \\
& + \underbrace{\text{information cost} + \text{markup}}_{\geq 0}
\end{aligned}
\tag{G.15}
$$

Besides the interest rate, we can also consider which system results in a higher overall consumer surplus, which captures both the interest rate and the ability to obtain a loan at all. In particular, the consumer surplus is the expected difference between the consumer's willingness to pay and the actual payment in states where a loan is provided. For passive intermediation, the consumer surplus is simply $A - \underline{R}(\lambda_d) = A - (\rho + \omega\lambda_d)$.

For active intermediation, the consumer surplus is zero when there are no lenders that are willing to lend since the consumer's outside option is normalized to zero, and it is also zero if there is only one willing lender since it charges an interest rate that is equal to the consumer's willingness to pay. By contrast, the consumer surplus is generally positive when there are at least 2 willing lenders. The consumer surplus can be summarized as follows:[59]

$$\pi_C = \underbrace{0 * E_{s_{n:n},s_{n-1:n}}\left[1_{\{s_{n:n}\leq \underline{s}\}}\right]}_{\text{no consumer surplus when zero willing lenders}}$$
$$+ \underbrace{E_{s_{n:n},s_{n-1:n}}\left[(A-A)1_{\{s_{n:n}\geq \underline{s}\geq s_{n-1:n}\}}\right]}_{\text{no consumer surplus when only 1 willing lender}}$$
$$+ \underbrace{E_{s_{n,n},s_{n-1:n}}\left[\left(A-\underline{R}(D(s_{n-1:n},s_{n-1:n};\psi,n))\right)1_{\{s_{n-1:n}\geq \underline{s}\}}\right]}_{\text{generally positive surplus when at least 2 willing lenders}} \tag{G.16}$$

Finally, we can also consider the total surplus, which is the sum of consumer surplus and lender profits:

$$S = n\pi_L + \pi_C \tag{G.17}$$

For passive intermediation, the total surplus is simply equal to the consumer surplus $A - \underline{R}(\lambda_d) = A - (\rho + \omega\lambda_d)$ since lenders make zero profits. For active intermediation, we can compute the total surplus using equations (F.13) and (G.16). To compare the surplus in active and passive intermediation, it is helpful to observe that the former can be simplified as

$$S^{\text{active}} = E_{s_{n:n},s_{n-1:n}}\left[\left(A - \underbrace{\underline{R}(D(s_{n:n},s_{n-1:n};\psi,n))}_{\text{origination cost}}\right)1_{\{s_{n:n}\geq \underline{s}\}}\right] - n\mu\frac{(\psi-z)^2}{2}. \tag{G.18}$$

Hence the difference between active and passive intermediation can be written as

$$S^{\text{active}} - S^{\text{passive}} = \underbrace{E_{s_{n:n},s_{n-1:n}}\left[(\underline{R}(\lambda_d) - \text{origination cost})\,1_{\{s_{n:n}\geq \underline{s}\}}\right]}_{\geq 0 \text{ superior screening}} \underbrace{-n\mu\frac{(\psi-z)^2}{2}}_{\leq 0 \text{ info. cost}}, \tag{G.19}$$

which can be either positive or negative depending on whether the benefit of superior screening outweighs the total information cost.

[59]See Internet Appendix I.6 for a calculation of consumer surplus.

G.2 Model results

Figure J.1 compares active and passive intermediation for varying degrees of λ_d. For low levels of risk, active intermediaries do not reject any applications. In that case, active intermediation exhibits the same default rate and origination cost as passive intermediation. However, lenders still screen the consumer to determine the interest rate, and disparities in the assessment of the consumer's risk provide an opportunity for lenders to obtain markups. Therefore, active intermediation is associated with a higher interest rate compared to passive intermediation. The figure also illustrates that the opportunity to obtain markups creates an incentive for lenders to improve their screening processes, which allows them to obtain higher markups as consumer risk increases.

For sufficiently high λ_d, active intermediaries start to reject applications, resulting in a reduction of the default rate compared to passive intermediation. This in turn leads to a reduction in the origination cost compared to passive intermediation, which can be large enough to also lead to a relative reduction in the overall interest rate compared to passive intermediation.

Additionally, as λ_d becomes sufficiently high, the ability to obtain markups generally decreases since the origination cost increases while the maximum interest rate that a lender can charge is fixed at the consumer's willingness to pay A. This in turn dampens the incentive for lenders to acquire information. If λ_d becomes too high, then lenders lose the incentive to invest in screening technology at all, causing them to leave the market. However, for consumers with high observable risk, active intermediaries are more likely to offer lower interest rates or lend at all compared to passive intermediaries.

Figure J.2 compares the total surplus generated by active and passive intermediation. Active intermediation has a slightly lower total surplus for low to intermediate levels of λ_d. In this region, lenders have an incentive to acquire information in order to obtain markups, but the rate at which they screen out risky consumers is relatively limited compared to the acquisition cost. For higher levels of λ_d, information acquisition leads lenders to more substantively reduce origination costs, in which case the benefit of superior screening outweighs the acquisition cost.

H Alternative model with heterogeneous lenders

This section presents versions of the model with heterogeneous lenders. We find that the differences between banks and nonbanks are consistent with the latter having a lower expected loss given default and consider the implications for the increasing market share of nonbanks.

H.1 Heterogeneous ψ

For simplicity, we assume that there are only 2 lenders with exogenous information levels ψ_1 and $\psi_2 < \psi_1$. Since the information levels are exogenous, we abstract from the information cost. The presentation of the model in this section is brief and focuses on differences relative to the model in Internet Appendix F.

The posterior risk of default conditional on receiving signal s_i with information level ψ_i is directly analogous to equation (F.3) and can be expressed as

$$D(s_i;\psi_i) \equiv Pr(d|s_i;\psi_i) = \lambda_d + \left(\frac{1}{2} - s_i\right)\psi_i \tag{H.1}$$

The posterior risk conditional on the lender's own signal and inferring from the equilibrium interest rate the signal of the competing lender becomes[60]

$$D(s_1,s_2;\psi_1,\psi_2) \equiv Pr(d|s_1,s_2;\psi_1,\psi_2) \underset{\psi\approx 0}{\approx} \lambda_d + \left(\frac{1}{2} - s_1\right)\psi_1 + \left(\frac{1}{2} - s_2\right)\psi_2 \tag{H.2}$$

As before, there is an equilibrium in which each lender's interest rate offer is based on the minimum posterior risk of default that it could have conditional on supplying the loan and updating its posterior risk based on the equilibrium outcome.[61] The *minimum* posterior risk conditional on winning for lender i occurs when the competing lender has the same posterior risk, which can be expressed as[62]

$$D(s_i,s_i;\psi_i,\psi_i) = \lambda_d + (1-2s_i)\,\psi_i \tag{H.3}$$

There is an equilibrium in which each lender's interest rate offer is equal to the zero-profits interest rate corresponding to the minimum posterior risk conditional on being equal to the zero-profits interest rate corresponding to the minimum posterior risk conditional on being chosen by the consumer (see equation (H.3)).[63]

[60] See Internet Appendix K.1 for a calculation.

[61] See Internet Appendix K.2 for a proof.

[62] Recall from equation (H.8) that the posterior risk for lender i is $\lambda_d + \left(\frac{1}{2} - s_i\right)\psi_i$. Therefore, if lender $-i$ has the same posterior risk as lender i then we must have $\left(\frac{1}{2} - s_{-i}\right)\psi_{-i} = \left(\frac{1}{2} - s_i\right)\psi_i$. Substituting this into equation (H.2) obtains equation (H.3).

[63] See Internet Appendix K.2 for a proof.

Proposition H.1. *A lender's interest rate offer is equal to*

$$\underline{R}(D(s_i, s_i; \psi_i, \psi_i)) = \omega \left[\lambda_d + (1 - 2s_i)\, \psi_i\right] + \rho \tag{H.4}$$

If only one lender makes an offer, it charges the maximum possible interest rate, A.

Each lender offers a loan on the condition that it will achieve nonnegative expected profits after learning about the action of the other lender from the equilibrium outcome. We consider an equilibrium in which each lender has a threshold $\underline{s}_i$ such that it makes an offer when $s_i \geq \underline{s}_i$. We determine $\underline{s}_i$ as the signal at which a lender would achieve zero expected profits assuming the other lender does not make an offer. This determines the following participation threshold.[64]

Proposition H.2. *A lender's participation threshold is equal to*

$$\underline{s}_i = \frac{2}{3}\left[\frac{\psi_1 + \psi_2}{2\psi_i} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_i}\right] \tag{H.5}$$

If $\underline{s}_{-i} \geq 1$ (where $\underline{s}_{-i}$ is the signal of the other lender), then $\underline{s}_i$ is instead given by

$$\underline{s}_i = \frac{1}{2} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_i} \tag{H.6}$$

Figure K.1 shows the probability of receiving credit from the more or less informed lender as well as outcomes associated with the two types of lenders for varying levels of λ_d.[65] The more informed lender is associated with a greater willingness to provide credit, which generally becomes more pronounced for riskier consumers. The more informed lender is also associated with a lower default rate and origination cost as well as a higher markup. In this case, the more informed lender is associated with a lower average interest rate for low λ_d consumers but a higher interest rate for high λ_d consumers.

H.2 Heterogeneous ω

In this section, we assume there are 2 lenders with the same exogenous ψ but different degrees of the expected loss given default: $\omega_2 < \omega_1$. Furthermore, we assume that the lender with lower loss given default has a higher cost of funding in order to maintain the property that the two lenders are equally competitive in the benchmark case of no

[64] See Internet Appendix K.3 for a proof.

[65] Note that λ_d starts a point greater than 0 due to the constraint $\psi \leq 2\lambda_d$ as described in Internet Appendix F.3.1.

screening:[66]

$$\rho_2 = \rho_1 + \lambda_d(\omega_1 - \omega_2) \tag{H.7}$$

In particular, this implies that the expected origination costs without screening for the two lenders satisfy $\rho_1 + \omega_1\lambda_d = \rho_2 + \omega_2\lambda_d$. As in Internet Appendix H.1, we abstract from the information cost since the information level is exogenous.

The posterior risk of default conditional on receiving signal s_i with information level ψ is directly analogous to equation (F.3) and can be expressed as

$$\begin{aligned} D(s_i;\psi) &\equiv Pr(d|s_i;\psi) \\ &= \lambda_d + \left(\frac{1}{2} - s_i\right)\psi \end{aligned} \tag{H.8}$$

The posterior risk conditional on the lender's own signal and inferring from the equilibrium interest rate the signal of the competing lender becomes[67]

$$\begin{aligned} D(s_1, s_2;\psi) &\equiv Pr(d|s_1, s_2;\psi) \\ &\underset{\psi\approx 0}{\approx} \lambda_d + (1 - s_1 - s_2)\,\psi \end{aligned} \tag{H.9}$$

Lender i's zero-profit interest rate is then

$$\underline{R}_i(D(s_1, s_2;\psi)) = \omega_i\left[\lambda_d + (1 - s_1 - s_2)\,\psi\right] + \rho_i \tag{H.10}$$

In contrast to the baseline model and the version with heterogeneous ψ, the version with heterogeneous ω is not a common value auction. As a result, we take a different strategy to derive the bid functions. In particular, we consider the space of linear bid functions $B_i(s_i) = a_i + b_i s_i$ and suppose that each lender chooses a_i and b_i in order to maximize its expected profits over realizations of the other lender's bid:

$$E_{s_{-i}}\left[\left(B_{-i}(s_{-i}) - \underline{R}_i(D(s_1, s_2;\psi))\right)1_{a_i + b_i s_i < B_{-i}(s_{-i})}\right] \tag{H.11}$$

This determines the following equilibrium.[68]

[66] We later show in Internet Appendix H.3 that our empirical results are consistent with nonbanks having a lower loss given default. Hence, this assumption is consistent with nonbanks also having a higher cost of funding (Buchak et al. (2018).

[67] This follows from the proof in Internet Appendix I.3 for the case of 2 lenders.

[68] See Internet Appendix K.4 for a proof.

Proposition H.3. *There is an equilibrium in which the bidding strategies are given by*

$$B_i(s_i) = \omega_i \left[\lambda_d + \omega_i \left(\frac{1}{2} - s_i\right) \psi\right] + \rho_i \tag{H.12}$$

Additionally, each lender offers a loan on the condition that it will achieve nonnegative expected profits after learning about the action of the other lender from the equilibrium outcome. We consider an equilibrium in which each lender has a threshold $\underline{s}_i$ such that it makes an offer when $s_i \geq \underline{s}_i$. We determine $\underline{s}_i$ as the signal at which a lender would achieve zero expected profits assuming the other lender does not make an offer. This determines the following participation threshold.[69]

Proposition H.4. *A lender's participation threshold is equal to*

$$\underline{s}_i = \frac{2}{3}\left[1 + \frac{2\omega_{-i} - \omega_i}{\omega_1\omega_2} \frac{(\omega_i\lambda_d + \rho_i - A)}{\psi}\right] \tag{H.13}$$

If $\underline{s}_{-i} \geq 1$ (where $\underline{s}_{-i}$ is the signal of the other lender), then $\underline{s}_i$ is instead given by

$$\underline{s}_i = \frac{1}{2} + \frac{\omega_i\lambda_d + \rho - A}{\omega_i\psi} \tag{H.14}$$

Figure K.2 shows the probability of receiving credit from the lender with greater or lower loss given default as well as outcomes associated with the two types of lenders for varying levels of λ_d. In this case, the lender with lower loss given default is associated with a greater willingness to provide credit, which generally becomes more pronounced for riskier consumers. The lender with lower loss given default is also associated with a higher default rate, origination cost, and overall interest rate.

H.3 Comparison of model with heterogeneous lenders and empirical observations

The empirical observations comparing banks and nonbanks are most consistent with nonbanks having a lower expected loss given default ω:

1. The upper left subfigure of Figure K.2 shows that lenders with lower ω tend to lend relatively more to observably risky consumers, which matches the observation that nonbanks exhibit higher observable risk (see Figure 7a).

[69] See Internet Appendix K.5 for a proof.

2. The middle left subfigure of Figure K.2 shows that lenders with lower ω tend to have a higher interest rate, which matches the observation that nonbanks exhibit higher interest rates conditional on observable risk (see Figure 7b).

3. The upper right subfigure of Figure K.2 shows that lenders with lower ω tend to have higher default rates conditional on observable risk, which matches the observation that nonbanks exhibit more defaults conditional on observable risk (see Figure 7c).

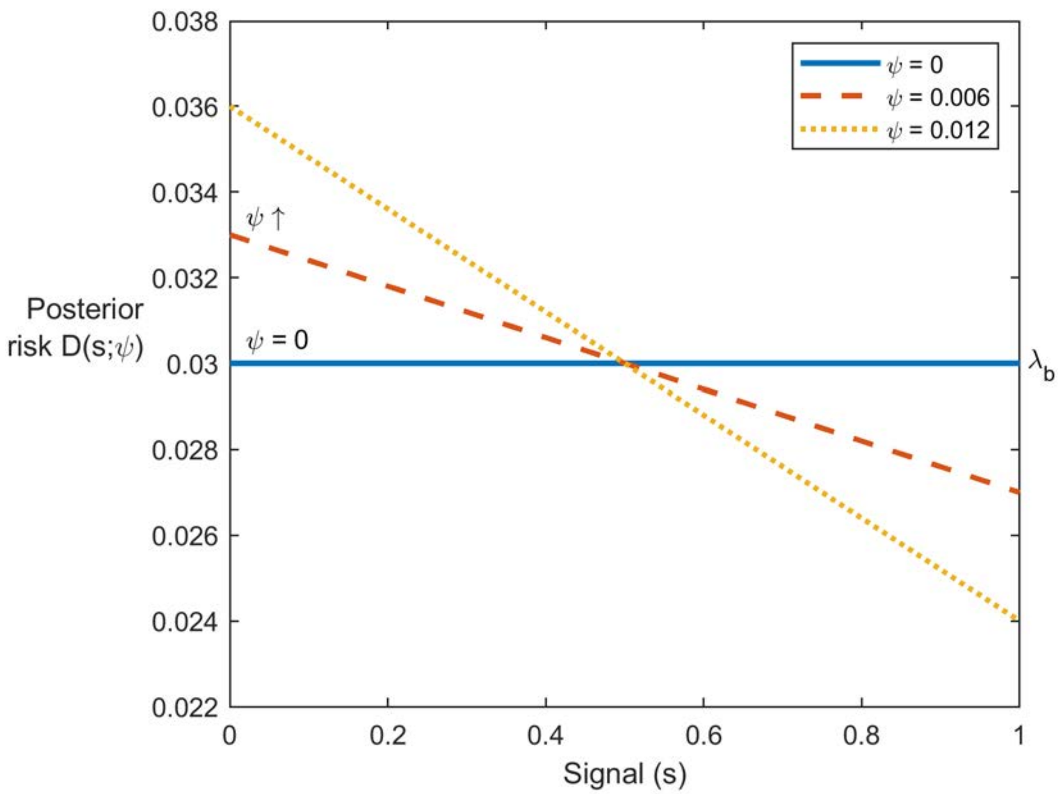
By contrast, the empirical results are not consistent with banks and nonbanks having heterogeneous ψ. In particular, Figure K.1 shows that lenders with lower ψ tend to lend relatively more to observably risk consumers but also tend to have lower default rates conditional on observable risk, which does not fit the profile of either banks or nonbanks.

I Proofs and supplemental material for the alternative model (Section F)

I.1 Illustration of risk estimation

Figure I.1: Posterior risk conditional on one signal

This figure shows how a lender's posterior risk $D(s;\psi)$ varies with its signal s and information level ψ.



I.2 Proof of Proposition F.1

This section shows that there is an equilibrium in which each lender's offered interest rate is $\underline{R}(D(s,s;\psi,n))$, where $\underline{R}(D)$ introduced in equation (F.7) is the zero-profits interest rate corresponding to the lender's probability of default D, $D(s,t;\psi,n)$ introduced in equation (F.4) is the posterior probability of default conditional on the signals of the supplying lender and the next most competitive lender, and in particular $D(s,s;\psi,n)$ introduced in equation (F.5) is the minimum posterior probability of default that a lender could have conditional on winning the auction and updating its risk estimate based on the equilibrium outcome.[70] By substituting in equation (F.5), note that $\underline{R}(D(s,s;\psi,n)) = \omega\left[\lambda_d + \frac{1}{2}(n-(n+2)s)\psi\right] + \rho$. Without loss of generality, we show that incentive compatibility holds for lender $i = 1$.

Note that a lender's interest rate offer only affects its expected profits insofar as it determines when it wins the auction. That is, conditional on winning the auction, a lender's own interest rate offer has no effect on its expected profits, and similarly in the case where the lender does not win the auction. Therefore, it suffices to check that if a lender wins an auction then it achieves positive expected profits (and therefore cannot profitably deviate by bidding a higher interest rate in order to lose), and if it loses the auction then it cannot profitably deviate by bidding a lower interest rate in order to win.

First, suppose lender 1 wins the auction. Suppose without loss of generality that the equilibrium interest rate is given by lender 2's offered interest rate, or $R_{eq} = \omega[\lambda_d + \frac{1}{2}(n-(n+2)s_2)\psi] + \rho$. Lender 1 can therefore infer s_2 and update its zero-profits interest rate after learning the information contained within the equilibrium interest rate:

$$\underline{R}(D(s_1,s_2;\psi,n)) = \omega\left[\lambda_d + \frac{1}{2}(n-2s_1-ns_2)\right] + \rho. \tag{I.1}$$

Since lender 2's offered interest rate is higher, one can infer from equation (F.8) that $s_2 < s_1$. Therefore, lender 1's updated zero profits interest rate is less than R_{eq}, so lender 1's offer still achieves positive expected profits. Hence, lender 1 has no profitable deviation.

Now, suppose that lender 1 loses the auction. If lender 1 hypothetically knew lender 2's offer, it could infer s_2 and thereby update its zero-profits interest rate after learning the information contained within the equilibrium interest rate:

$$\underline{R}(D(s_1,s_2;\psi,n)) = \omega\left[\lambda_d + \frac{1}{2}(n-2s_1-ns_2)\right] + \rho. \tag{I.2}$$

Since lender 2's offer is lower, one can infer from equation (F.8) that $s_2 > s_1$. Therefore, lender 1's updated zero profits interest rate is greater than lender 2's offer, so lender 1 has no incentive to deviate by undercutting lender 2. Since this argument holds for all potential values of lender 2's offer, lender 1 can conclude that there is no profitable deviation even if it doesn't observe the equilibrium interest rate.

[70] If lender i wins, then the observation of the equilibrium interest rate will allow it to effectively observe the next most competitive lender, which will lead to an increase in lender i's estimated posterior risk of default since lender i wins only if it has a lower posterior probability of default conditional on its own signal. Hence, the minimum posterior probability of default that lender i can have conditional on winning and observing the equilibrium interest rate occurs when the next most competitive lender has the same posterior probability of default.

I.3 Calculation for equation (F.4)

This section shows

$$D(s,t;\psi,n) = \lambda_d + \frac{1}{2}(n-2s-nt)\,\psi$$

First, using general results about order statistics, note that the joint distribution of $s_{n:n}$ and $s_{n-1:n}$ for a consumer of type θ is given by

$$f(s_{n:n}=s, s_{n-1:n}=t|\theta) = n(n-1)F(t|\theta)^{n-2}f(t|\theta)f(s|\theta) \tag{I.3}$$

Then, observe that the predictive distribution for the joint distribution for the two highest signals is given by

$$\begin{aligned}
f(s_{n:n}=s, s_{n-1:n}=t) &= \lambda_d f(s_{n:n}=s, s_{n-1:n}=t|d) + \lambda_r f(s_{n:n}=s, s_{n-1:n}=t|r)\\
&= \lambda_d n(n-1)F(t|d)^{n-2}f(t|d)f(s|d) + \lambda_r n(n-1)F(t|r)^{n-2}f(t|r)f(s|r)\\
&= \lambda_d n(n-1)\left(t+\frac{1}{2}\left(t-t^2\right)\frac{\psi}{\lambda_d}\right)^{n-2}\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right)\\
&\quad+\lambda_r n(n-1)\left(t+\frac{1}{2}\left(t^2-t\right)\frac{\psi}{\lambda_r}\right)^{n-2}\left(1+\left(t-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right)\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right)\\
&\underset{\psi\approx 0}{\approx} \lambda_d n(n-1)\left(t^{n-2}+(n-2)t^{n-3}\frac{1}{2}\left(t-t^2\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right)\\
&\quad+\lambda_r n(n-1)\left(t^{n-2}+(n-2)t^{n-3}\frac{1}{2}\left(t^2-t\right)\frac{\psi}{\lambda_r}\right)\left(1+\left(t-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right)\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right)\\
&\underset{\psi\approx 0}{\approx} n(n-1)t^{n-2}
\end{aligned} \tag{I.4}$$

Then, by Bayesian inference we have

$$\begin{aligned}
D(s,t;\psi,n) &\equiv Pr(d|s_{n:n}=s, s_{n-1:n}=t)\\
&= \lambda_d\frac{f(s_{n:n}=s, s_{n-1:n}=t|d)}{f(s_{n:n}=s, s_{n-1:n}=t)}\\
&= \lambda_d\frac{n(n-1)F(t|d)^{n-2}f(t|d)f(s|d)}{n(n-1)t^{n-2}}\\
&= \lambda_d f(s|d)f(t|d;\psi)\left(\frac{F(t|d)}{t}\right)^{n-2}\\
&= \lambda_d\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+\frac{1}{2}(1-t)\frac{\psi}{\lambda_d}\right)^{n-2}\\
&\underset{\psi\approx 0}{\approx} \lambda_d\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+(n-2)\frac{1}{2}(1-t)\frac{\psi}{\lambda_d}\right)\\
&\underset{\psi\approx 0}{\approx} \lambda_d+\frac{1}{2}(n-2s-nt)\,\psi
\end{aligned} \tag{I.5}$$

I.4 Proof of Proposition F.2

This section shows

$$\underline{s} = \frac{n}{n+1} + \frac{2(\omega\lambda_d + \rho - A)}{(n+1)\omega\psi}$$

The threshold is defined by the point where a lender's expected profits are equal to zero.

To compute this, consider that if the supplying lender's signal is equal to $\underline{s}$, then, by symmetry, no other lender offers a loan.[71] Therefore, the supplying lender charges an interest rate A and has an expected zero-profits interest rate of $E_{s_{n-1:n}}[\underline{R}(D(\underline{s}, s_{n-1:n}; \psi, n))|s_{n:n} = \underline{s}]$.

To compute the latter, recall that the predictive distribution of the signal is uniform. Therefore, the conditional pdf for the greatest signal among the $n-1$ competing draws is given by $f(s_{n-1:n} = t|s_{n:n} = s) = (n-1)\frac{t^{n-2}}{s^{n-1}}$. Therefore

$$\begin{aligned} E_{s_{n-1:n}}[s_{n-1:n}|s_{n:n} = \underline{s}] &= \int_0^{\underline{s}} t\left[(n-1)\frac{t^{n-2}}{\underline{s}^{n-1}}\right] dt \\ &= \frac{n-1}{n}\underline{s} \end{aligned} \tag{I.6}$$

Therefore, we have

$$\begin{aligned} E_{s_{n-1:n}}[\underline{R}(D(\underline{s}, s_{n-1:n}; \psi, n))|s_{n:n} = \underline{s}] &= \omega\left[\lambda_d + \frac{1}{2}\left(n - 2\underline{s} - nE_{s_{n-1:n}}[s_{n-1:n}|s_{n:n} = \underline{s}]\right)\right] + \rho \\ &= \omega\left[\lambda_d + \frac{1}{2}(n - (n+1)\underline{s})\psi\right] + \rho \end{aligned} \tag{I.7}$$

Finally, as mentioned above, $\underline{s}$ is the point where a lender has zero expected profits, which is determined by the condition:

$$\begin{aligned} 0 &= A - E_{s_{n-1:n}}[\underline{R}(D(\underline{s}, s_{n-1:n}; \psi, n))|s_{n:n} = \underline{s}] \\ &= A - \left[\omega\left[\lambda_d + \frac{1}{2}(n - (n+1)\underline{s})\psi\right] + \rho\right] \end{aligned} \tag{I.8}$$

I.5 Calculation for equation (F.13)

This section computes lender profits.

First, recall that the predictive distribution of the signal is uniform. Therefore, the con-

[71] We ignore the zero-probability event where multiple lenders have the same signal.

ditional pdf for the greatest signal among the $n-1$ competing draws is given by $f(s_{n-1:n} = t|s_{n:n} = s) = (n-1)\frac{t^{n-2}}{s^{n-1}}$. Therefore, modulo the cost of information acquisition, a lender's expected profit conditional on winning with signal s can be written as

$$\begin{aligned}
\pi_L(s) &= E_{s_{n-1:n}}\left[(A - \underline{R}(D(s, s_{n-1:n}; \psi, n)))\, 1_{\{s=s_{n:n}, s_{n-1:n}\leq \underline{s}\}}\right] \\
&\quad + E_{s_{n-1:n}}\left[(\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) - \underline{R}(D(s, s_{n-1:n}; \psi, n)))\, 1_{\{s=s_{n:n}, s_{n-1:n}\geq \underline{s}\}}\right] \\
&= \int_0^{\underline{s}} (A - \omega\lambda_d - \rho)(n-1)\frac{t^{n-2}}{s^{n-1}} dt \\
&\quad - \omega\psi\frac{1}{2}\int_0^{\underline{s}} (n - 2s - nt)(n-1)\frac{t^{n-2}}{s^{n-1}} dt \\
&\quad + \int_{\underline{s}}^{s} \omega(s-t)\psi(n-1)\frac{t^{n-2}}{s^{n-1}} dt \\
&= (A - \omega\lambda_d - \rho)\underline{s}^{n-1}\frac{1}{s^{n-1}} \\
&\quad + \omega\psi\frac{1}{2}\left[(n-1)\underline{s}^n + 2s\underline{s}^{n-1} - n\underline{s}^{n-1}\right]\frac{1}{s^{n-1}} \\
&\quad + \omega\psi\left[\frac{1}{n}s^n - s\underline{s}^{n-1} + \frac{n-1}{n}\underline{s}^n\right]\frac{1}{s^{n-1}}
\end{aligned} \tag{I.9}$$

Then, the pdf for the maximum signal is given by $f(s_{n:n}) = ns^{n-1}$. Integrating over potential values of the maximal signal $s_{n:n} \in [\underline{s}, 1]$ and dividing by n to obtain the profits for a single lender, modulo the cost of information acquisition, results in

$$\begin{aligned}
\pi_L &= \frac{1}{n}\int_{\underline{s}}^{1} \pi_L(s) n s^{n-1} ds \\
&= (A - \omega\lambda_d - \rho)\underline{s}^{n-1}(1 - \underline{s}) \\
&\quad + \omega\psi\frac{1}{2}\left[(-n+1)\underline{s}^{n-1} + (2n-1)\underline{s}^n - n\underline{s}^{n+1}\right] \\
&\quad + \omega\psi\left[\frac{1}{n(n+1)} - \frac{1}{2}\underline{s}^{n-1} + \frac{n-1}{n}\underline{s}^n + \frac{-n+1}{2(n+1)}\underline{s}^{n+1}\right]
\end{aligned} \tag{I.10}$$

Finally, a lender's total profits are obtained by subtracting out the information acquisition cost $\mu\frac{(\psi-z)^2}{2}$.

I.6 Calculation for equation (G.17)

This section computes consumer surplus.

First, observe that a consumer only achieves a positive surplus if $s_{n-1:n} \geq \underline{s}$. In particular, if $s_{n-1:n} < \underline{s}$ then either the consumer doesn't obtain a loan and receives the outside option of zero (if $s_{n:n} < \underline{s}$) or it obtains a loan with an interest rate equal to its willingness to pay and therefore also achieves a net surplus of zero (if $s_{n:n} \geq \underline{s}$). Therefore, the consumer surplus is given by

$$\begin{aligned}
\pi_C &= E_{s_{n-1:n}} \left[\{A - \underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)\} \, 1_{\{s_{n-1:n} \geq \underline{s}\}} \right] \\
&= E_{s_{n-1:n}} \left[\left\{ A - \left(\omega \left[\lambda_d + \frac{1}{2} \left(n - (n+2) s_{n-1:n} \right) \psi \right] + \rho \right) \right\} 1_{\{s_{n-1:n} \geq \underline{s}\}} \right] \\
&= (A - \omega \lambda_d - \rho) E_{s_{n-1:n}} \left[1_{\{s_{n-1:n} \geq \underline{s}\}} \right] \\
&\quad - E_{s_{n-1:n}} \left[\frac{1}{2} \omega \left(n - (n+2) s_{n-1:n} \right) \psi 1_{\{s_{n-1:n} \geq \underline{s}\}} \right]
\end{aligned} \tag{I.11}$$

Recall that the predictive distribution of the signal is uniform. Therefore, the conditional pdf for $n-1$ order statistic among the n signals is given by $f(s_{n-1:n} = t) = n(n-1)(1-t)t^{n-2}$. Then computing the expectations determines

$$\begin{aligned}
\pi_C &= (A - \omega \lambda_d - \rho)(1 - n\underline{s}^{n-1} + (n-1)\underline{s}^n) \\
&\quad - \frac{1}{2} \omega \psi \left[\frac{2}{n+1} - n^2 \underline{s}^{n-1} + 2(n-1)(n+1)\underline{s}^n - \frac{n(n-1)(n+2)}{n+1} \underline{s}^{n+1} \right]
\end{aligned} \tag{I.12}$$

J Results for the alternative model (Internet Appendix G)

Figure J.1: Active and passive intermediation

These figures show various features of the model of active intermediation (the baseline model in which lenders screen the applicant, approve or deny the application, and engage in imperfect competition to determine the interest rate) and passive intermediation (a setting where all applications approved by the AUS are originated and the interest rate is determined by a zero-profits condition) for various levels of λ_d. The *probability of receiving credit* is the probability that at least one lender approves the application. The *default rate* is the fraction of approved applications that consist of defaulting consumers. The *interest rate* is the average interest payment divided by the probability of receiving credit. The interest rate for active intermediation is decomposed as the *origination cost* (which is the zero-profits interest rate of the supplying lender conditional on its own signal and inferring from the equilibrium the signal of the next most competitive lender), the *information cost* (which is the cost associated with the parameter ψ corresponding to the quality of screening), and a residual *markup* (which corresponds to a lender's total expected total profits). *Pr(1 offer | receiving credit)* is the probability that the consumer receives only one offer conditional on receiving credit. Parameters: $\rho = 0$, $n = 2$, $A = .0027$, $\omega = .066$, $\mu = .1$.

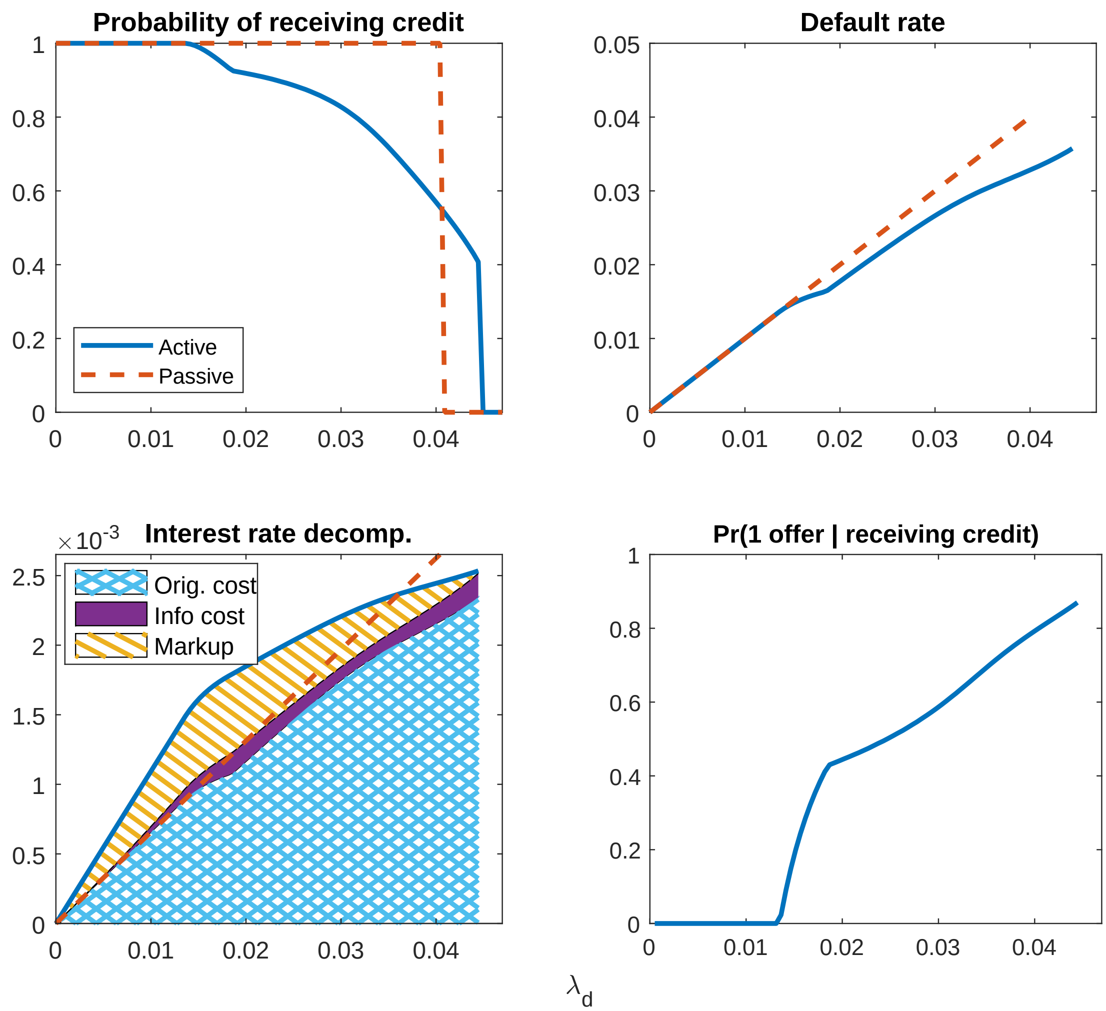
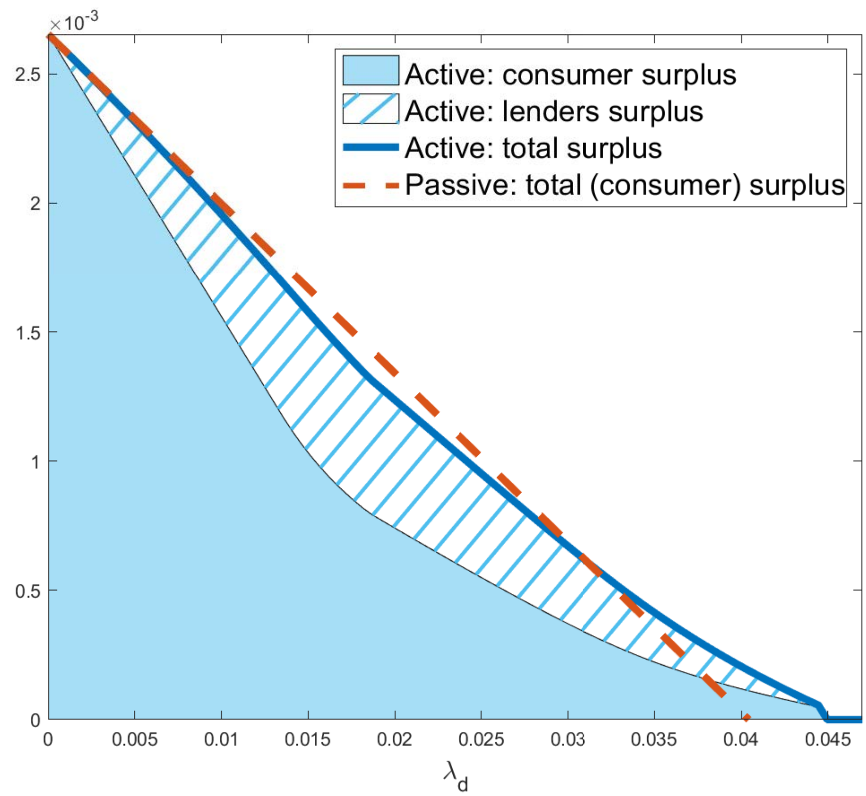


Figure J.2: Surplus decomposition

This figure shows the total surplus for active intermediation (the baseline model in which lenders screen the applicant, approve or deny the application, and engage in imperfect competition to determine the interest rate) and passive intermediation (a setting where all applications approved by the AUS are originated and the interest rate is determined by a zero-profits condition) for various levels of λ_d. It also shows the divide of the surplus between consumers and lenders for active intermediation. Note that in passive intermediation the surplus is entirely accrued by the consumer. Parameters: $\rho = 0$, $n = 2$, $A = .0027$, $\omega = .066$, $\mu = .1$.



K Proofs for heterogeneous lenders in the alternative model (Internet Appendix H)

K.1 Calculation for equation (H.2)

This section shows

$$D(s_1, s_2; \psi_1, \psi_2) \underset{\psi\approx 0}{\approx} \lambda_d + \left(\frac{1}{2} - s_1\right)\psi_1 + \left(\frac{1}{2} - s_2\right)\psi_2$$

First, since the signals are independently distributed, observe that the pdf of the predictive distribution of the two signals can be written as

$$\begin{aligned}
f(s_1, s_2; \psi_1, \psi_2) &= \lambda_d f(s_1|d;\psi_1) f(s_2|d;\psi_2) + \lambda_r f(s_2|r;\psi_1) f(s_2|r;\psi_2) \\
&= \lambda_d \left(1 + \left(\frac{1}{2} - s_1\right)\frac{\psi_1}{\lambda_d}\right)\left(1 + \left(\frac{1}{2} - s_2\right)\frac{\psi_2}{\lambda_d}\right) \\
+ \quad & \lambda_r \left(1 + \left(s_1 - \frac{1}{2}\right)\frac{\psi_1}{\lambda_r}\right)\left(1 + \left(s_2 - \frac{1}{2}\right)\frac{\psi_2}{\lambda_r}\right) \\
&\underset{\psi\approx 0}{\approx} \lambda_d \left[1 + \left(\frac{1}{2} - s_1\right)\frac{\psi_1}{\lambda_d} + \left(\frac{1}{2} - s_2\right)\frac{\psi_2}{\lambda_d}\right] \\
&\quad + \lambda_r \left[1 + \left(s_1 - \frac{1}{2}\right)\frac{\psi_1}{\lambda_r} + \left(s_2 - \frac{1}{2}\right)\frac{\psi_2}{\lambda_r}\right] \\
&= 1
\end{aligned} \tag{K.1}$$

Then, by Bayesian inference and independence we have

$$\begin{aligned}
D(s_1, s_2; \psi_1, \psi_2) &\equiv Pr(d|s_1, s_2; \psi_1, \psi_2) \\
&= \lambda_d \frac{f(s_1, s_2|d; \psi_1, \psi_2)}{f(s_1, s_2; \psi_1, \psi_2)} \\
&= \lambda_d \frac{f(s_1|d;\psi_1) f(s_2|d;\psi_2)}{f(s_1, s_2; \psi_1, \psi_2)} \\
&= \lambda_d \left(1 + \left(\frac{1}{2} - s_1\right)\frac{\psi_1}{\lambda_d}\right)\left(1 + \left(\frac{1}{2} - s_2\right)\frac{\psi_2}{\lambda_d}\right) \\
&\underset{\psi\approx 0}{\approx} \lambda_d + \left(\frac{1}{2} - s_1\right)\psi_1 + \left(\frac{1}{2} - s_2\right)\psi_2
\end{aligned} \tag{K.2}$$

K.2 Proof of Proposition H.1

This section shows that there is an equilibrium in which each lender's offer is $\underline{R}(D(s_i, s_i; \psi_i, \psi_i))$, where $\underline{R}(D)$ introduced in equation (F.7) is the zero-profits interest rate corresponding to the lender's probability of default D, $D(s_1, s_2; \psi_1, \psi_2)$ introduced in equation (H.2) is the posterior probability of default conditional on the signals of both lenders, and in particular $D(s_i, s_i; \psi_i, \psi_i)$ introduced in equation (F.5) is the minimum posterior probability of default that a lender could have conditional on winning the auction and updating its risk estimate based on the equilibrium outcome.[72] By substituting in equation (F.5), note that $\underline{R}(D(s_i, s_i; \psi_i, \psi_i)) = \omega\left[\lambda_d + (1-2s_i)\psi_i\right] + \rho$. Without loss of generality, we show that incentive compatibility holds for $i = 1$.

Note that a lender's interest rate offer only affects its expected profits insofar as it determines when it wins the auction. That is, conditional on winning the auction, a lender's own interest rate offer has no effect on its expected profits, and similarly in the case where the lender does not win the auction. Therefore, it suffices to check that if a lender wins an auction then it achieves positive expected profits (and therefore cannot profitably deviate by bidding a higher interest rate in order to lose), and if it loses the auction then it cannot profitably deviate by bidding a lower interest rate in order to win.

First, suppose lender 1 wins the auction. Note that the equilibrium interest rate must then be given by lender 2's offer, or $R_{eq} = \omega[\lambda_d + (1-2s_2)\psi_2] + \rho$. Lender 1 can therefore infer $\left(\frac{1}{2} - s_2\right)\psi_2 = \frac{\frac{R_{eq}-\rho}{\omega} - \lambda_d}{2}$ and update its zero-profits interest rate after learning the information contained within the equilibrium interest rate:

$$\underline{R}(D(s_1, s_2; \psi_1, \psi_2)) = \omega\left[\lambda_d + \left(\frac{1}{2} - s_1\right)\psi_1 + \left(\frac{1}{2} - s_2\right)\psi_2\right] + \rho. \tag{K.3}$$

Since lender 2's offer is higher, one can infer from equation (H.4) that $(1-2s_2)\psi_2 > (1-2s_1)\psi_1$. Therefore, lender 1's updated zero profits interest rate is less than R_{eq}, so lender 1's offer still achieves positive expected profits. Hence, lender 1 has no profitable deviation.

Now, suppose that lender 1 loses the auction. If lender 1 hypothetically knew lender 2's offer, it could infer $\left(\frac{1}{2} - s_2\right)\psi_2 = \frac{\frac{R_{eq}-\rho}{\omega} - \lambda_d}{2}$ and thereby update its zero-profits interest rate after learning the information contained within the equilibrium interest rate: $\underline{R}(D(s_1, s_2; \psi_1, \psi_2)) = \omega\left[\lambda_d + \left(\frac{1}{2} - s_1\right)\psi_1 + \left(\frac{1}{2} - s_2\right)\psi_2\right] + \rho$. Since lender 2's offer is lower, one can infer from equation (H.4) that $(1-2s_2)\psi_2 < (1-2s_1)\psi_1$. Therefore, lender 1's updated zero profits interest rate is greater than lender 2's offer, so lender 1 has no incentive to deviate by undercutting lender 2. Since this argument holds for all potential values of lender 2's offer, lender 1 can conclude that there is no profitable deviation even if

[72] If lender i wins, then the observation of the equilibrium interest rate will allow it to effectively observe the signal of lender $-i$, which will lead to an increase in lender i's estimated posterior risk of default since lender i wins only if it has a lower posterior probability of default conditional on its own signal. Hence, the minimum posterior probability of default that lender i can have conditional on winning and observing the equilibrium interest rate occurs when lender $-i$ has the same posterior probability of default.

it doesn't observe the equilibrium interest rate.

K.3 Proof of Proposition H.2

This section shows

$$\underline{s}_i = \frac{2}{3}\left[\frac{\psi_1 + \psi_2}{2\psi_i} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_i}\right] \tag{K.4}$$

The threshold is defined by the point where a lender's expected profits is equal to zero under the assumption that the other lender does not compete. First, consider the case of lender 1.

To compute $\underline{s}_1$, consider that, given that lender 2 will not compete, the lender 1 charges an interest rate A and has expected zero-profits interest rate of

$$E_{s_2}[\underline{R}(D(s_1, s_2; \psi_1, \psi_2))|s_2 < \underline{s}_2].$$

To compute the latter, recall that the predictive distribution is uniform. Therefore, the conditional pdf for s_2 is given by $f(s_2|s_2 < \underline{s}_2) = \frac{1}{\underline{s}_2}$. Therefore

$$\begin{aligned} E[s_2|s_2 < \underline{s}_2] &= \int_0^{\underline{s}_2} \frac{s_2}{\underline{s}_2} ds_2 \\ &= \frac{1}{2}\underline{s}_2 \end{aligned} \tag{K.5}$$

Therefore, we have

$$\begin{aligned} E_{s_2}[\underline{R}(D(s_1, s_2; \psi_1, \psi_2))|s_2 < \underline{s}_2] &= \omega\left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi_1 + \left(\frac{1}{2} - E_{s_2}[s_2|s_2 < \underline{s}_2]\right)\right] + \rho \\ &= \omega\left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi_1 + \left(\frac{1}{2} - \frac{1}{2}\underline{s}_2\right)\right] + \rho \end{aligned} \tag{K.6}$$

Finally, as mentioned above, $\underline{s}_1$ is the point where lender 1 has zero expected profits, which is determined by the condition:

$$\begin{aligned} 0 &= A - E_{s_2}[\underline{R}(D(s_1, s_2; \psi_1, \psi_2))|s_2 < \underline{s}_2] \\ &= A - \left[\omega\left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi_1 + \left(\frac{1}{2} - \frac{1}{2}\underline{s}_2\right)\right] + \rho\right] \end{aligned} \tag{K.7}$$

An analogous equation also holds for lender 2. Then the system of equations implies the result.

Note that if $\underline{s}_2 \geq 1$, then lender 2 never makes an offer, and therefore lender 1 cannot make any inferences about s_2 based on the observation that lender 2 does not make an offer. In that case, $\underline{s}_1$ is instead defined by

$$
\begin{aligned}
& 0 = A - \left[\omega\left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi_1\right] + \rho\right] \\
\Longrightarrow \ & \underline{s}_1 = \frac{1}{2} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_1}
\end{aligned}
\tag{K.8}
$$

An analogous argument determines $\underline{s}_2$ when $\underline{s}_1 \geq 1$.

K.4 Proof of Proposition H.3

This section shows that, if we consider the space of linear bid functions of the form $B_i(s_i) = a_i + b_i s_i$, and, conditional on drawing signal s_i, lender i chooses a_i and b_i in order to maximize the expected profits

$$
E_{s_{-i}}\left[\left(B_{-i}(s_{-i}) - \underline{R}_i(D(s_1, s_2; \psi))\right) 1_{a_i + b_i s_i < B_{-i}(s_{-i})}\right] \tag{K.9}
$$

then there is an equilibrium in which the bid functions are given by

$$
B_i(s_i) = \omega_i\left[\lambda_d + \omega_i\left(\frac{1}{2} - s_i\right)\psi\right] + \rho_i \tag{K.10}
$$

Without loss of generality, consider the decision problem of lender 1 conditional on lender 2 playing the corresponding equilibrium bid function. That is, lender 1 chooses a_1 and b_1 while the coefficients for lender 2's bid function are $a_2 = \omega_2\left[\lambda_d + \frac{1}{2}\psi\right] + \rho_2$ and $b_2 = -\omega_2\psi$.

Given s_1, denote the threshold value of s_2 at which lender 1 wins the auction by $\tilde{s}_2(s_1)$, i.e., $B_1(s_1) = B_2(\tilde{s}_2(s_1))$. Note that if $\tilde{s}_2(s_1) \geq 1$ then marginal changes in lender 1's bid function have no effect on its expected profits since lender 1 always wins and pays the interest rate determined by lender 2's bid. Similarly, if $\tilde{s}_2(s_1) \leq \underline{s}_2$ (note that the participation threshold $\underline{s}_2$ is defined in equation (H.13)) then marginal changes in lender 1's bid function have no effect on its expected profits since it always loses regardless of lender 2's signal. Therefore, consider the case where $\tilde{s}_2(s_1) \in (\underline{s}_2, 1)$. In that case, lender 1's problem is to find a_1 and b_1 to maximize

$$\int_0^{\underline{s}_2} \left[A - \left[\omega_1 \left[\lambda_d + (1 - s_1 - s_2)\, \psi\right] + \rho_1\right]\right] ds_2 \\ + \int_{\underline{s}_2}^{\tilde{s}_2(s_1)} \left[(a_2 + b_2 s_2) - \left[\omega_1 \left[\lambda_d + (1 - s_1 - s_2)\, \psi\right] + \rho_1\right]\right] ds_2 \tag{K.11}$$

Note that a_1 and b_1 only affect the expected profits through $\tilde{s}_2(s_1)$. Therefore, the first order condition for either a_1 or b_1 implies

$$\tilde{s}_2(s_1) = \frac{\omega_1 \left[\lambda_d + \psi\right] + \rho_1 - a_2}{b_2 + \omega_1 \psi} - \frac{\omega_1 \psi}{b_2 + \omega_1 \psi} s_1 \tag{K.12}$$

Then the condition $B_1(s_1) = B(\tilde{s}_2(s_1))$ implies

$$\begin{aligned} a_1 + b_1 s_1 &= a_2 + b_2 \tilde{s}_2(s_1) \\ &= a_2 + \frac{b_2 \left(\omega_1 \left[\lambda_d + \psi\right] + \rho_1 - a_2\right)}{b_2 + \omega_1 \psi} - \frac{b_2 \omega_1 \psi}{b_2 + \omega_1 \psi} s_1 \end{aligned} \tag{K.13}$$

This implies

$$\begin{aligned} b_1 &= -\frac{b_2 \omega_1 \psi}{b_2 + \omega_1 \psi} \\ &\underset{\psi \approx 0}{\approx} -\omega_1 \psi \end{aligned} \tag{K.14}$$

and

$$\begin{aligned} a_1 &= a_2 + \frac{b_2 \left(\omega_1 \left[\lambda_d + \psi\right] + \rho_1 - a_2\right)}{b_2 + \omega_1 \psi} \\ &\underset{\psi \approx 0}{\approx} \omega_1 \lambda_d + \omega_1 \psi + \frac{\omega_1}{b_2} (a_2 - \omega_1 \lambda - \rho_1) \\ &\underset{b_2 = -\omega_2 \psi}{=} \omega_1 \lambda_d + \omega_1 \psi - \frac{\omega_1}{\omega_2} (a_2 - \omega_1 \lambda_d - \rho_1) \\ &\underset{a_2 = \omega_2 \left[\lambda_d + \frac{1}{2}\psi\right] + \rho_2}{=} \omega_1 \left[\lambda_d + \frac{1}{2} \psi\right] + \rho_1 \end{aligned} \tag{K.15}$$

Therefore, the described bid function is incentive compatible for lender 1.

K.5 Proof of Proposition H.4

This section shows

$$\underline{s}_i = \frac{2}{3}\left[1 + \frac{2\omega_i - \omega_{-i}}{\omega_1\omega_2}\frac{(\omega_i\lambda_d + \rho_i - A)}{\psi}\right] \tag{K.16}$$

The threshold is defined by the point where a lender's expected profits are equal to zero under the assumption that the other lender does not compete. First, consider the case of lender 1.

To compute $\underline{s}_1$, consider that, given that lender 2 will not compete, lender 1 charges an interest rate A and has expected zero-profits interest rate of $E_{s_2}[\underline{R}_1(D(s_1, s_2; \psi))|s_2 < \underline{s}_2]$.

Recall that the predictive distribution is uniform. Therefore, the conditional pdf for s_2 is given by $f(s_2|s_2 < \underline{s}_2) = \frac{1}{\underline{s}_2}$. Therefore

$$\begin{aligned} E[s_2|s_2 < \underline{s}_2] &= \int_0^{\underline{s}_2} \frac{s_2}{\underline{s}_2} ds_2 \\ &= \frac{1}{2}\underline{s}_2 \end{aligned} \tag{K.17}$$

Therefore, we have

$$\begin{aligned} E_{s_2}[\underline{R}_1(D(s_1, s_2))|s_2 < \underline{s}_2] &= \omega_1\left[\lambda_d + \left(1 - \underline{s}_1 - E_{s_2|s_2<\underline{s}_2}\right)\psi\right] + \rho_1 \\ &= \omega_1\left[\lambda_d + \left(1 - \underline{s}_1 - \frac{1}{2}\underline{s}_2\right)\psi\right] + \rho_1 \end{aligned} \tag{K.18}$$

Finally, as mentioned above, $\underline{s}_1$ is the point where lender 1 has zero expected profits, which is determined by the condition:

$$\begin{aligned} 0 &= A - E_{s_2}[\underline{R}_1(D(s_1, s_2))|s_2 < \underline{s}_2] \\ &= A - \left[\omega_1\left[\lambda_d + \left(1 - \underline{s}_1 - \frac{1}{2}\underline{s}_2\right)\psi\right] + \rho_1\right] \end{aligned} \tag{K.19}$$

An analogous equation also holds for lender 2. Then the system of equations implies the result.

Note that if $\underline{s}_2 \geq 1$, then lender 2 never makes an offer, and therefore lender 1 cannot make any inferences about s_2 based on the observation that lender 2 does not make an offer.

In that case, $\underline{s}_1$ is instead defined by

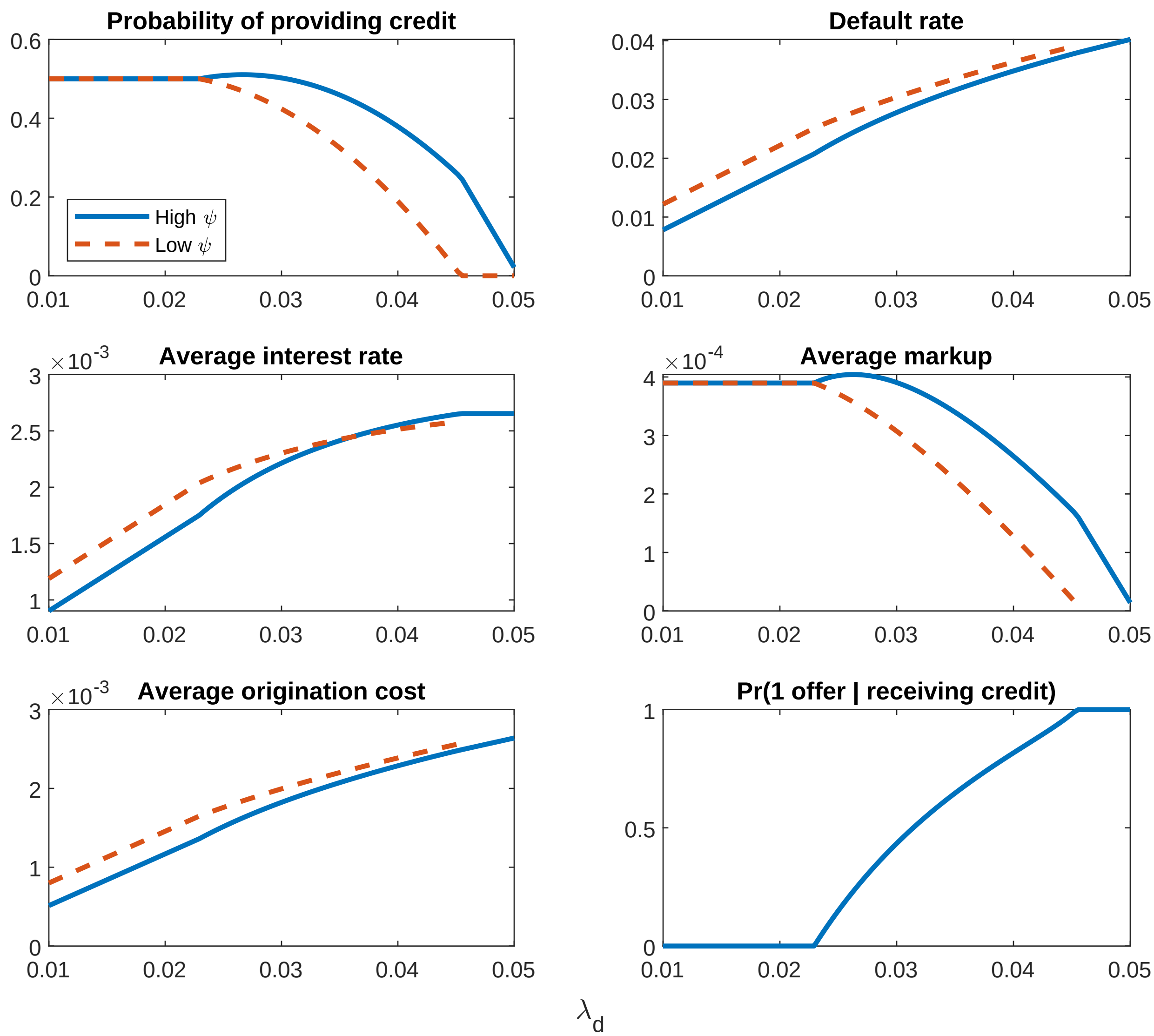
$$
\begin{aligned}
0 &= A - \left[\omega_1 \left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi\right] + \rho\right] \\
\implies \underline{s}_1 &= \frac{1}{2} + \frac{\omega_1 \lambda_d + \rho - A}{\omega_1 \psi}
\end{aligned}
\tag{K.20}
$$

An analogous argument determines $\underline{s}_2$ when $\underline{s}_1 \geq 1$.

K.6 Results for heterogeneous ψ (Internet Appendix H.1)

Figure K.1: Active intermediation with heterogeneous ψ

These figures show various features of the version of the model with 2 lenders with exogenous and different information levels ψ (described in Internet Appendix H.1). The *probability of receiving credit* is the probability that at least one lender approves the application. The *default rate* is the fraction of approved applications that consist of defaulting consumers. The *average interest rate* is the average interest payment divided by the probability of receiving credit. The *average origination cost* is the average zero-profits interest rate of the supplying lender conditional on its own signal and inferring from the equilibrium the signal of the next most competitive lender. The *average markup* is a lender's total expected profits (average interest rate - average origination cost). *Pr(1 offer | receiving credit)* is the probability that the consumer receives only one offer conditional on receiving an offer. Parameters: $\rho = 0$, $n = 2$, $A = .0027$, $\omega = .066$, $\mu = .1$, $\psi = .015$ and .02.



K.7 Results for heterogeneous ω (Internet Appendix H.2)

Figure K.2: Active intermediation with heterogeneous ω

These figures show various features of the version of the model with 2 lenders with exogenous and the same information levels ψ but different losses given default ω (described in Internet Appendix H.2). The *probability of receiving credit* is the probability that at least one lender approves the application. The *default rate* is the fraction of approved applications that consist of defaulting consumers. The *average interest rate* is the average interest payment divided by the probability of receiving credit. The *average origination cost* is the average zero-profits interest rate of the supplying lender conditional on its own signal and inferring from the equilibrium the signal of the next most competitive lender. The *average markup* is a lender's total expected profits (average interest rate - average origination cost). *Pr(1 offer | receiving credit)* is the probability that the consumer receives only one offer conditional on receiving an offer. Parameters: $n = 2$, $A = .0027$, $\omega = .066$ and $.04$, $\rho = 0$ for high ω and given by equation (H.7) for low ω, $\mu = .01$, $\psi = .02$.