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# THE VALUE OF INTERMEDIARIES FOR GSE LOANS

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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. These findings are explained using a model of competitive lending in which lenders have skin-in-the-game and acquire information beyond the GSEs' underwriting criteria, but also charge markups. We find that most borrowers are better off in a counterfactual in which the GSEs' underwriting criteria are implemented passively. Finally, 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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An internet appendix is available at http://www.nber.org/data-appendix/w31575

# 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 offer? We specifically focus on a trade-off in which intermediaries reduce the cost of lending by screening out borrowers that 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 can also charge markups. We further consider which types of borrowers would benefit (or not) from changes in the role or nature of intermediaries, such as a market in which the discretionary behavior of intermediaries is eliminated or a market dominated by either banks or nonbanks.

We approach these questions using proprietary regulatory data on all loans acquired by the GSEs during 2016-2017, a period for which we can precisely observe the guarantee fees, or g-fees, that the GSEs charge to insure a loan. We document a series of observations about lenders' discretionary overlays on the intensive and extensive margins. Our first observation is that interest rates increase with measures of ex-ante observable default risk. In particular, a one percentage point increase in the probability of default as predicted by the borrower's credit score, LTV ratio, and DTI ratio is associated with a 9 basis point increase in interest rates net of g-fees. This result suggests that lenders independently add a risk spread to the interest rate and is consistent with lenders having skin-in-the-game, or a positive loss given default, due to the threat of repurchases and exclusion from

[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.

the GSEs.[3]

Our second observation is that interest rates net of g-fees also predict ex-post defaults even after controlling for ex-ante observable risk characteristics. In particular, a one percentage point increase in the interest rate net of g-fees is associated with a 35 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 57 basis points. This result is robust to capturing observable risk via not only the credit score, LTV, and DTI 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.

We perform several robustness exercises to confirm these results. A potential alternative explanation for the second observation is that higher interest rates directly increase default risk. However, our third observation is that interest rates actually have a relatively modest direct effect on default. To isolate this direct effect from other channels linking interest rates and defaults, including risk-based pricing, we examine how default rates vary with changes in interest rates induced by variation in the g-fee conditional on observable risk.[4] We find that a one percentage point increase in the interest rate induced by the g-fee is only associated with a 3 basis point and statistically insignificant increase in the default rate, which is small compared to the association reported in the second observation. We also show that our first two observations are robust to the use of discount points by considering a lender's total origination revenue instead of the interest rate, where the former incorporates a lender's income from selling loans on the secondary market as well as closing costs.

Finally, while we focus primarily on the intensive margin of overlays, we also investigate the extensive margin using loan application data. Similar to Bhutta, Hizmo, and Ringo (2021), we find that lender denials are not fully determined by the GSEs' automated

[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 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.

[4] Here, 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. 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 levels of observable risk as measured by these characteristics as well as variation in observable risk associated with the DTI ratio.

underwriting systems. In particular, we show that the rate at which lenders deny applications that are accepted by the GSEs' automated underwriting systems increases with observable risk.

Equipped with the above empirical findings, we then develop a model of mortgage lender competition with screening that explains these observations and leverages them 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. For example, this could correspond to penalties imposed by the GSEs, such as repurchases or restrictions on the ability to continue doing business as a counterparty. Second, motivated by evidence of lenders also pricing for default risk that is not captured by observable risk characteristics, lenders in the model have the ability to implement further screening to determine if they will offer a loan and, if so, how much of a risk spread they will charge in addition to the GSEs' g-fees. Third, lenders can charge a markup due to limited competition, which is consistent with recent evidence of noncompetitive pricing in the mortgage market (e.g. Bhutta, Fuster, and Hizmo (2021) and Alexandrov and Koulayev (2018)).

We leverage the model to compare the status quo in which lenders exercise discretionary overlays to a counterfactual in which there is no screening beyond the requirements of the GSEs. That is, in the counterfactual all applications that are accepted by the GSE underwriting criteria are offered a loan with a zero-profits interest rate conditional on the borrower's observable risk.[5] On the one hand, discretionary screening by lenders could lead to lower interest rates since screening out risky borrowers reduces costs. On the other hand, it could lead to higher interest rates since disparities in lenders' estimates of the risk, combined with limited competition, can provide an opportunity for them to charge markups. Overall, we find that the former channel dominates for borrowers with high observable risk while the latter channel dominates for the majority of borrowers with low to medium levels of observable risk. We also find a similar pattern when instead considering the combined surplus of consumers and lenders: the combination of lender market power and discretionary screening leads to lower overall welfare in the context of lending to observably safe borrowers but higher welfare for observably risky borrowers, which again primarily derives from the fact that the cost-saving benefit of screening increases with observable risk.

[5]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 requirements, which produces the same result as a market in which lenders face perfect competition. It can also be loosely likened to a market in which intermediaries are simply eliminated by allowing the GSEs to lend directly, although we do not focus on that interpretation since direct lending by the GSEs is prohibited.

While the primary question of this paper is about 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. We focus on nonbanks because their market share has increased significantly in the years following the crisis (Buchak et al. (2018)), which has raised questions about financial stability since they are associated with greater liquidity risk, less robust capital positions, and a stronger tendency to lend to relatively riskier borrowers (Kim et al. (2018), Kim et al. (2022)). We find that defaults for loans originated by nonbanks occur at more than one and a half times the corresponding rate for banks, which reflects a combination of nonbanks lending to observably riskier borrowers as well as exhibiting higher default rates conditional on observable risk. Consistent with their riskier credit profiles, nonbanks are also associated with higher interest rates conditional on observable risk. Finally, we present evidence that the presence of nonbank fintech lenders that use a mostly online application process, which have disproportionately contributed to the increasing market share of nonbanks, has been associated with banks targeting safer borrowers with lower default rates and lower interest rates.

The model suggests the observed differences between banks and nonbanks are more consistent with fundamental differences in the expected loss given default rather than screening quality. 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, if nonbanks implemented superior (or worse) screening, they would be expected to focus on observably riskier (safer) borrowers while also having lower (higher) default rates conditional on observable risk. One explanation is that banks more often have an incentive to protect rents from other business lines, whereas nonbanks, which typically have a monoline business model, may perceive declaring bankruptcy as a less costly limit on losses.[6] An implication of this result is that the increasing market share of nonbanks may lead to an increase in mortgage default rates, although such an increase would still be limited by the GSEs' automated underwriting systems.[7]

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 (Bhutta, Hizmo, and Ringo (2021), Bartlett et al.

[6]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.

[7]The effect of the increasing market share of nonbanks on interest rates and markups depends on additional assumptions about other loan production costs, such as funding costs.

(2022), and Giacoletti, Heimer, and Yu (2022)), regulations (Fuster, Plosser, and Vickery (2021), Defusco, Johnson, and Mondragon (2020)), repurchases and servicing costs (Goodman (2017)), fair pricing and credit allocation by region (Hurst et al. (2016) and Kulkarni (2016)), and capacity constraints (Fuster, Lo, and Willen (2017)). We contribute by providing evidence that lenders price for risk on GSE loans in a manner independent of the GSEs' g-fees, consistent with an intensive margin of overlays. Based on our model, we find that intermediaries are more likely to reduce interest rates (compared to a benchmark with passive intermediation) for observably risky borrowers due to their screening incentive, although they result in higher interest rates for the majority of borrowers.

Second, this paper contributes to the literature on the role of nonbanks in mortgage lending (Buchak et al. (2018), Buchak et al. (2022), Kim et al. (2018), Gete and Reher (2020), and Kim et al. (2022)), including fintechs in particular (Fuster et al. (2019) and Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021)). We show that nonbanks are associated with higher default rates and interest rates even conditional on observable risk. 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 differences 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)), the relationship between competition and underwriting quality (Yannelis and Zhang (2021)), 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), Farboodi et al. (2019)). We develop a model of mortgage lender competition with screening that decomposes mortgage interest rates into components corresponding to the cost of funding, risk spreads, and markups. Based on our model, we conclude that markups account for a relatively greater portion of interest rates for observably safe borrowers compared to observably risky borrowers.

The rest of the paper is organized as follows. Section 2 provides evidence that lenders charge risk spreads on GSE loans, consistent with an intensive margin of overlays. Section 3 develops a model in which lenders' discretionary overlays result from conducting additional screening beyond the GSEs' underwriting criteria and retaining a positive loss given default. Section 4 shows that the discretionary behavior of lenders can lead to lower interest rates for observably risky borrowers but higher interest rates for observably safe borrowers due to the conflicting effects of superior screening and opportunities to charge markups. Section 5 shows that the observed differences between banks and nonbanks are more consistent with differences in their expected loss given default rather than screening quality and examines the implications if the mortgage market becomes increasingly dominated by nonbank lenders. Section 6 concludes.

# 2 Empirical observations

This section first shows that interest rates net of g-fees, as well as origination revenues, in the GSE segment of the mortgage market positively correlate with both ex-ante observable risk and ex-post default, suggesting that lenders independently price for risk. It also shows that, compared to banks, nonbanks are associated with greater observable risk, greater default rates conditional on observable risk, and greater interest rates and origination revenue conditional on observable risk, consistent with nonbanks internalizing a lower loss given default.

## 2.1 Key definitions

We consider relationships involving interest rates, g-fees, origination revenue, ex-post default risk, ex-ante observable risk, and lender types, which we define in the context of our analysis as follows:

*Interest rate* is the annualized mortgage interest rate at origination.

*Guarantee fee*, or g-fee, refers to the cost that the GSEs charge for acquiring and guaranteeing a mortgage loan. 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 typically depends on the loan's general product type, whereas the upfront component typically depends 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.

*Origination revenue* refers to a lender's income from originating a loan, expressed as a percentage of the loan amount and not annualized. Similar to Zhang (2022), we compute origination revenue as the sum of two components: upfront closing costs and secondary market income. *Closing costs* is measured by *origination charges*, which we obtain by merging with the recently expanded HMDA data. *Secondary market 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 mortgage-backed securities (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]

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

Our computation of secondary market income is slightly different from Fuster, Lo, and Willen (2017) and Zhang (2022) in that we determine the premium relative to par using the 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 market income during 2018 was 3.3% (Table D.2), 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%

[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 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 market income $= (\text{interest rate} - \text{ongoing g-fee} - \text{MBS yield}) * \text{PVM} - \text{upfront g-fee}$.

per year, assuming a similar trend continued from 2014 to 2018. Finally, the average total origination revenue in our sample is 4.2%, 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 (average of 0.6% in our sample).

*Default* in the context of our analysis refers to 90-day delinquency within 2 years of origination.

*Observable risk* is the estimated probability of default based on (that is, is observable with respect to) 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 the upfront g-fee (60% or less, 60.01-70%, 70.01-75%, 75.01-80%, 80.01-85%, 85.01-90%, 90.01-95%, and greater than 95%), and DTI bins corresponding to quintiles. Note that the *credit score* for a loan refers to the "representative credit score" that is used to determine the g-fee. This is defined as 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.

*Banks* refers to depositories.

*Nonbanks* refers to lenders that are not banks.

*Fintechs* refers to lenders with a mostly online application process. We use the designation of fintechs in Fuster et al. (2019)). 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.[12] The tables and figures in 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 we start to have precise data on g-fees, 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

[12]While we only focus on GSE loans, we find based on the National Mortgage Database, a sample of residential mortgages maintained by the FHFA and the Consumer Financial Protection Bureau, that GSE loans account more than 85% of total origination volume of conventional conforming loans meeting analogous sample restrictions to those in our main sample.

2018, which we merge with the expanded HMDA data to obtain information on origination charges.[13] 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 where the upfront portion of the g-fee approximately only depends on the LTV ratio and credit score. In particular, we restrict to fixed rate, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses. We also exclude high balance loans exceeding the national baseline conforming loan limit and loans with subordinate financing. 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.

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

## 2.3 Interest rates net of g-fees and denials increase with default risk

Observations 1-3 show that interest rates net of g-fees are positively associated with observable risk and unobservable risk (i.e. default risk conditional on observable risk) to a degree that exceeds their direct effect on default. Observation 4 shows using application data that denial rates on applications also increase with observable risk.

### 2.3.1 Observation 1: interest rates net of g-fees increase with observable risk

Figure 1 shows observable risk is positively associated with interest rates, even after subtracting out the g-fee. Similarly, Table 1 column (1) shows that interest rates are positively associated with observable risk while also controlling for ZIP code by year-quarter fixed effects based on the origination date. Decomposing the components of observable risk, column (2) shows that interest rates are negatively associated with credit score and positively associated with the loan-to-value (LTV) ratio and the debt-to-income (DTI) ratio. Column (3) and column (4) show that these results are only partially mitigated by subtracting out the total g-fee. Based on the estimate in column (3), a 1 percentage point increase in the ex-ante probability of default is associated with a 9.4 basis point increase in the interest rate net of g-fees. Column (5) shows that the association is stronger for loans with LTV less than or equal to 80%, in which case the GSEs do not require private

[13]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.

mortgage insurance, while column (6) shows that the association is weaker for loans with LTV greater than 80%, in which case the GSEs do require private mortgage insurance.

These results suggest that lenders independently price for default risk, possibly due to repurchases or other penalties imposed by the GSEs. Section 3 incorporates this result into a model of mortgage lender competition with screening by supposing that lenders bear a positive expected loss given default.

As additional robustness, Figure D.1 in Internet Appendix D.2 shows using the 2018 sample that origination revenue is also associated with observable risk. It also shows that this association is primarily driven by secondary market income, whereas closing costs are comparatively constant with respect to observable risk. Column (1) and column (2) of Table D.3, also in Internet Appendix D.2, show that origination revenue is associated with observable risk and its constituent factors while controlling for ZIP code by year-quarter fixed effects. Columns (3)-(6) show that the closing costs portion and the secondary market income are also both increasing in observable risk on average, although the latter is much stronger and appears to drive the overall association between origination revenue and observable risk.

Additionally, Table D.4 in Internet Appendix D.2 shows using an analogous dataset derived from Optimal Blue that the results are qualitatively similar when controlling for lock rate date fixed effects instead of ZIP code by year-quarter fixed effects, which better helps to control for potential changes in the composition of borrowers associated with short-term fluctuations in interest rates.[14],[15]

#### 2.3.2 Observation 2: interest rates net of g-fees predict default conditional on observable risk

Figure 2 shows that interest rates net of g-fees are positively associated with default rates, even after controlling for observable risk. Similarly, Table 2 column (1) shows that interest rates are predictive of default while also controlling for ZIP code by year-quarter fixed effects, while column (2) shows that this relationship continues to hold even after controlling for observable risk. Column (3) shows that it also continues to hold after controlling for a host of additional observable characteristics, including the interaction between 10-

[14] Note that Optimal Blue does not have a multiplier to convert the upfront g-fee to an annualized rate, so we instead include fixed effects for the expected upfront g-fee as a function of credit score and LTV based on the first table of the GSEs' g-fee matrix.

[15] Generalizing these results from the GSE segment of the market, Table D.5 in Internet Appendix D.2 shows 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.

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 year-month fixed effects. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

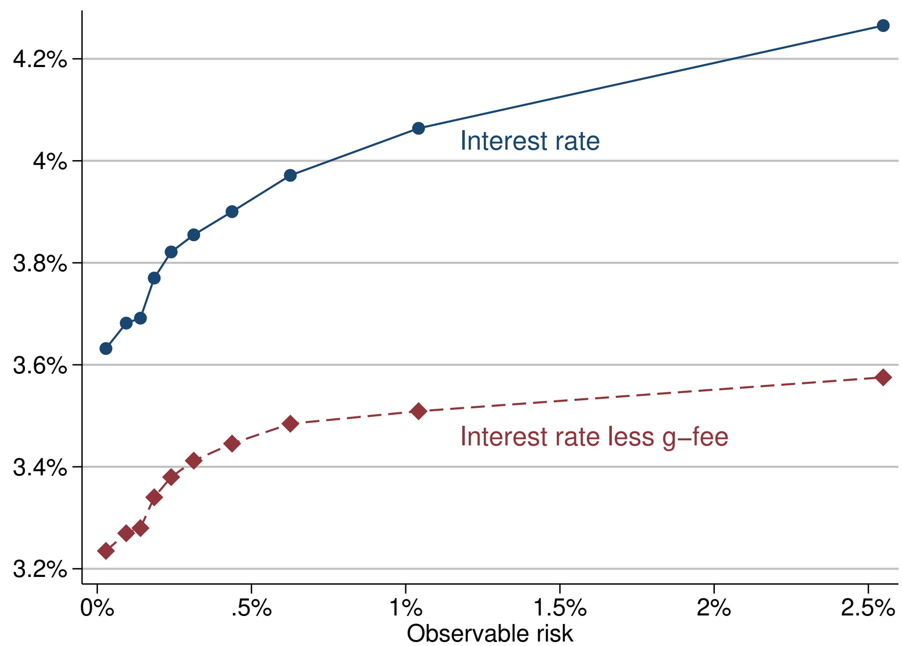


Table 1: Interest rates and observable risk

| | (1) IR | (2) IR | (3) IR - g-fee | (4) IR - g-fee | (5) LTV<=80 | (6) LTV>80 |
|---|---|---|---|---|---|---|
| Observable risk | 0.206*** | | 0.094*** | | 0.119*** | 0.059*** |
| | (647.97) | | (340.86) | | (214.17) | (189.56) |
| Credit score | | -0.299*** | | -0.125*** | | |
| | | (-562.96) | | (-261.29) | | |
| LTV | | 0.741*** | | 0.497*** | | |
| | | (440.84) | | (330.76) | | |
| DTI | | 0.274*** | | 0.277*** | | |
| | | (106.07) | | (119.46) | | |
| Observations | 2,109,041 | 2,109,041 | 2,109,041 | 2,109,041 | 851,576 | 1,219,780 |
| $R^2$ | 0.492 | 0.547 | 0.496 | 0.535 | 0.486 | 0.539 |
| ZIP $\times$ Year-quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |

Note: Column (1) regresses the interest rate on observable risk while controlling for ZIP code by year-quarter fixed effects. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the debt-to-income ratio as described in Section 2.1. Column (2) regresses the interest rate on the 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 interest rate net of the total g-fee. Column (5) and column (6) are similar to column (3) except restricting to loans with LTV less than or equal to 80% or LTV greater than 80%, respectively. 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

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 absorbs observable risk); income decile indicators; family type indicators (i.e. single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; term indicators; appraisal value decile indicators; an indicator for a loan having an interest-only period; an indicator for a refinance loan; loan amount decile indicators; an indicator for self-employed borrowers; an indicator for first-time homebuyers; an indicator for full income documentation; and an indicator for full asset documentation.

Based on the estimate in column (2), a 1 percentage point increase in the interest rate net of g-fees is associated with a 35 basis point increase in the default rate conditional on observable risk, which is substantial compared to the overall default rate of 57 basis points. Column (4) shows that the association between interest rates and default 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, particularly for observably riskier borrowers. This is consistent with existing evidence 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 3 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 D.2 and Table D.6 in Internet Appendix D.3 show that default is also positively associated with origination revenue in 2018, notwithstanding the effects of COVID-19 on loan performance.

#### 2.3.3 Observation 3: interest rates have a relatively small direct effect on default

An alternative explanation for Observation 2 is that higher interest rates might directly increase default risk. To estimate this direct effect, we examine how default rates vary with changes in interest rates induced by variation in the upfront g-fee while linearly controlling for observable risk. While the upfront g-fee is generally increasing with observable risk, residual variation could derive from the DTI ratio, which only affects the latter, as well as any cross-subsidization implicit in the upfront g-fee matrix. The exogeneity assumption is that the variation in the upfront g-fee while controlling for observable risk only affects default rates through the interest rate. For example, it is not correlated with any unobservable risk that might otherwise lead lenders to choose a higher interest rate.

Figure 2: 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 year-month fixed effects and observable risk. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

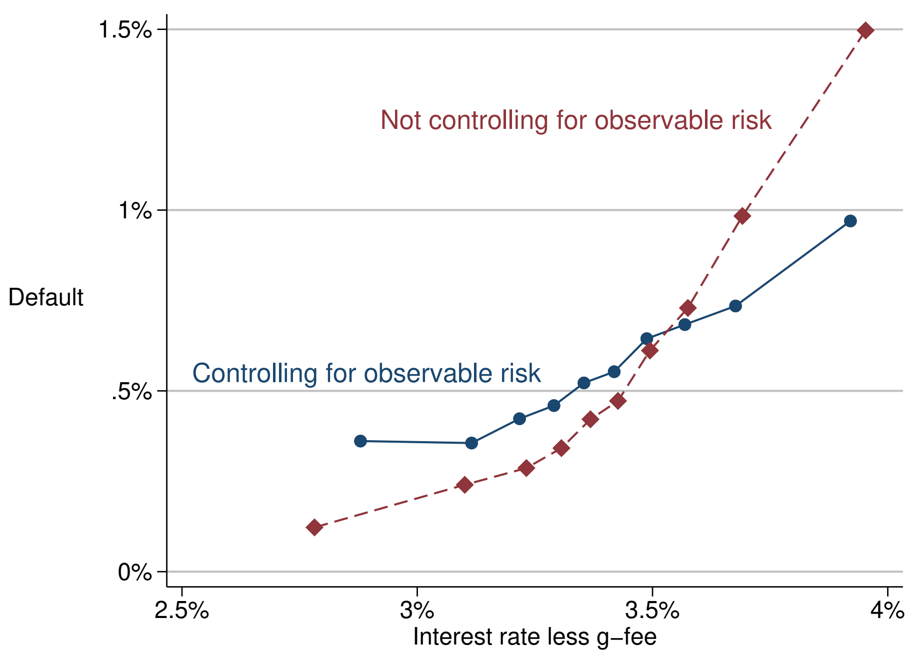


Table 2: Interest rates and default

| | (1) Baseline | (2) Obs. risk | (3) Controls | (4) Safe | (5) Risky | (6) Interact | (7) IR |
|---|---|---|---|---|---|---|---|
| IR - g-fee | 0.927*** | 0.346*** | 0.426*** | 0.129*** | 0.674*** | 0.129*** | |
| | (48.99) | (18.78) | (16.34) | (10.13) | (17.32) | (10.12) | |
| Obs. risk | | 0.928*** | | 0.716*** | 0.943*** | 0.716*** | 0.904*** |
| | | (63.71) | | (11.72) | (52.69) | (11.71) | (59.72) |
| IR - g-fee × Risky | | | | | | 0.545*** | |
| | | | | | | (13.31) | |
| Obs. risk × Risky | | | | | | 0.227*** | |
| | | | | | | (3.57) | |
| IR | | | | | | | 0.275*** |
| | | | | | | | (17.46) |
| Observations | 2,109,041 | 2,109,041 | 2,109,029 | 1,030,232 | 1,040,160 | 2,070,392 | 2,109,041 |
| $R^2$ | 0.092 | 0.100 | 0.103 | 0.137 | 0.137 | 0.140 | 0.100 |
| ZIP × Year-quarter FE | Yes | Yes | Yes | Yes | Yes | No | Yes |
| ZIP × Year-quarter × Risky FE | No | No | No | No | No | Yes | No |
| Controls | No | No | Yes | No | No | No | No |

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. Column (2) adds observable risk as a regressor. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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 absorbs observable risk); income decile indicators; family type indicators (i.e. single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; term indicators; appraisal value decile indicators; an indicator for a loan having an interest-only period; an indicator for a refinance loan; loan amount decile indicators; an indicator for self-employed borrowers; an indicator for first-time homebuyers; an indicator for full income documentation; and an indicator for full asset documentation. 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

Column (1) of Table 3 shows in a first-stage regression that the upfront g-fee strongly predicts interest rates while controlling for observable risk. Column (2) shows that a 1 percentage point increase in the interest rate induced by the upfront g-fee is only associated with a 3 basis point and statistically insignificant increase in the default rate, which is small compared to the overall association of 28 basis point reported in Column (7) of Table 2.[16] Column (3) and Column (4) show that this result is mostly similar on the subsets of safe and risky firms, as determined by whether observable risk is below or above the median.

Table 3: G-fee induced variation in interest rates and default

| | (1) First stage | (2) IV | (3) Safe | (4) Risky |
|---|---|---|---|---|
| Upfront g-fee | 0.216*** | | | |
| | (398.60) | | | |
| Obs. risk | 0.068*** | 0.954*** | 0.788*** | 0.970*** |
| | (153.65) | (36.16) | (9.94) | (32.22) |
| IR | | 0.030 | 0.045 | 0.051 |
| | | (0.31) | (1.17) | (0.35) |
| Observations | 2,109,041 | 2,109,041 | 1,030,232 | 1,040,160 |
| $R^2$ | 0.525 | 0.010 | 0.000 | 0.009 |
| ZIP × Year-quarter FE | Yes | Yes | Yes | Yes |
| Zip × Year-quarter × Risky FE | No | No | No | No |
| Controls | No | No | No | No |

Note: Column (1), the first stage, regresses the interest rate on the upfront g-fee and observable risk while controlling for ZIP code by year-quarter fixed effects. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the debt-to-income ratio as described in Section 2.1. Column (2) regresses an indicator for default (multiplied by 100) on the interest rate and observable risk, while the former is instrumented by the upfront g-fee. Column (3) estimates the specification in column (2) except restricting to relatively safe borrowers with observable risk below the median. Column (4) estimates the specification in column (2) 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

[16]This result is distinct from evidence in Fuster and Willen (2017) and Di Maggio et al. (2017) that payment reductions associated with interest rate resets on adjustable-rate mortgages decrease delinquencies. In particular, our result is about the ex-ante interest rate determined at origination, whereas these papers focus on ex-post changes.

#### 2.3.4 Observation 4: denials conditional on GSE approval increase with observable risk

For this observation, we use a comprehensive dataset of U.S. mortgage applications 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, purchase or no cash-out refinance 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 restrict to first lien mortgages. 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."[17] 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.[18] Note that we compute observable risk as a function of credit score, LTV, and DTI based on the model estimated with the MLIS data.[19]

Figure 3 shows that denials increase with observable risk, ranging from about 1.77% for borrowers with 0.07% observable risk to 7.22% for borrowers with 3.4% observable risk.

#### 2.3.5 Observations 1-4 interpretation and robustness

Consistent with an intensive margin of overlays, Observations 1-3 together suggest the interpretation that lenders charge a risk spread on GSE mortgages that is independent of the g-fee and that predicts default without directly increasing the propensity to default to the same degree. Consistent with an extensive margin of overlays, Observation 4 additionally shows that lenders deny riskier applications, even if they are accepted by the GSEs. Section 3 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.

Another possible interpretation for Observations 1-3 is that lenders may be pricing

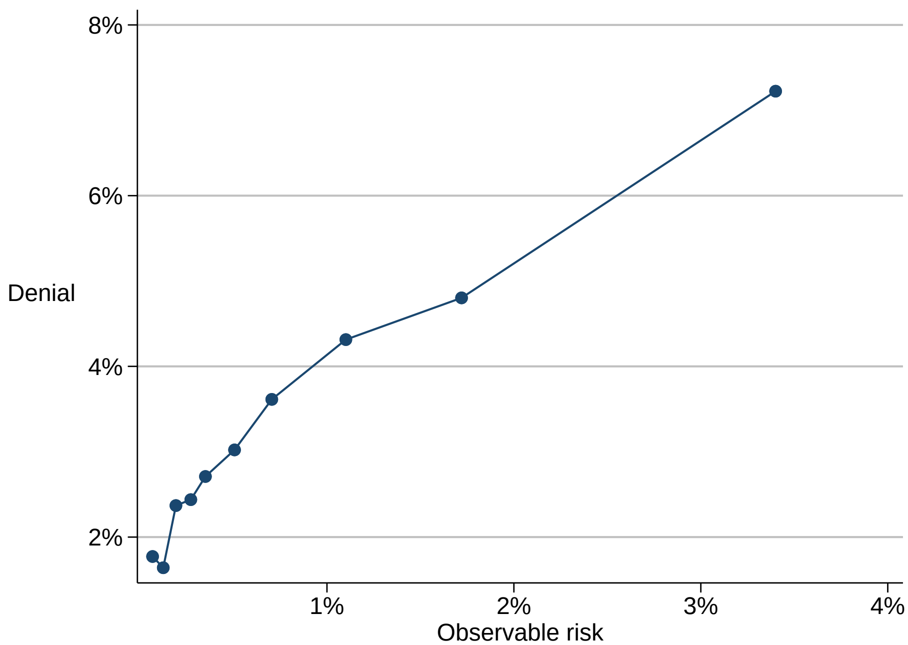
[17] Note that about 92.6% of the sample is processed by only one AUS. The results are similar if we restrict to mortgages that receive a response of "Approve/Eligible" or "Accept" by either Desktop Underwriter (for Fannie Mae) or Loan Prospector (Freddie Mac) for at least one AUS submission.

[18] 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 D.7 in Internet Appendix D.4 for the fraction of denials attributable to each reason before implementing this restriction.

[19] Note that we use the combined LTV since the mortgage application data does not have the original LTV for just the loan application.

Figure 3: 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 credit score, the loan-to-value ratio, and the debt-to-income ratio as described in Section 2.1, which is estimated using the MLIS data. Source: mortgage application data, 2018, restricting to applications accepted by the GSE automated underwriting systems for conventional, purchase or no cash-out refinance, first lien loan applications for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit.




for prepayment risk.[20] However, we account for prepayments in the following ways. First, 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 D.1 and Table D.3 in Internet Appendix D.2 as well as Figure D.2 and Table D.6 in Internet Appendix D.3 control for the use of discount points by considering total origination revenue, as discount points only shift the closing cost and secondary market

[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)).

income components without affecting the total. Second, borrowers with smaller loans may be less likely to refinance because closing costs are a larger fraction of the principal balance, but column (3) of Table 2 controls for the loan amount. Third, Table D.8 in Internet Appendix D.5 shows that controlling for observable prepayment risk, which is defined analogously to observable risk but based on prepayment within 2 years, has little effect on the association between interest rates and observable risk. Column (4) of Table D.8 further shows that our results are robust to controlling for intermediary fixed effects, meaning that the association between interest rates and observable risk occurs within intermediaries and is not driven by a correlation with intermediary-specific pricing. Table D.9 shows that controlling for observable prepayment risk also has little effect on the association between interest rates and default conditional on observable risk. Moreover, observable prepayment risk has virtually no association with default conditional on observable risk.

## 2.4 Variation in intermediation patterns by lender type

Strikingly, nonbanks exhibit a default rate that exceeds that of banks by more than 70% (0.75% for nonbank-nonfintechs and 0.78% for fintechs, respectively, compared to 0.44% for banks, as shown in Table D.1 in Internet Appendix D.1). To analyze this observation more closely, Observation 5 shows that nonbanks are associated with greater observable risk, while Observation 6 shows that nonbanks are also associated with higher default rates conditional on observable risk. Additionally, Observation 7 shows that nonbanks exhibit higher interest rates conditional on observable risk. Finally, Observation 8 shows that the presence of fintechs in particular is associated with a reduction in interest rates and defaults of competing banks.

### 2.4.1 Observation 5: nonbanks exhibit higher observable risk

Table 4 shows that nonbanks are associated with greater overall observable risk, with nonbank-nonfintechs having a 9 basis point higher default probability and fintechs having a 10 basis point higher default probability compared to banks purely on the basis of credit score, LTV, and DTI, which corresponds to a 17% or 19% increase relative to the corresponding probability for banks. In most cases, nonbanks are also associated with greater risk as measured by each component of observable risk. Summarizing these results graphically, Figure D.3 in Internet Appendix D.6 shows that the kernel density and cumulative distribution function of observable risk are slightly more concentrated at higher values for nonbanks compared to banks, while the histograms in Figure D.4 show that a similar comparison holds for the components of observable risk.

Table 4: Observable risk and lender type

(a) Banks

| | Mean | P10 | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|
| Observable risk (%) | 0.53 | 0.07 | 0.12 | 0.24 | 0.56 | 1.33 |
| Credit score | 753.18 | 689.00 | 725.00 | 762.00 | 789.00 | 803.00 |
| Loan-to-value (%) | 76.38 | 50.00 | 67.00 | 80.00 | 90.00 | 95.00 |
| Debt-to-income (%) | 32.72 | 19.39 | 25.52 | 33.32 | 40.54 | 44.57 |

(b) Nonbank-nonfintechs

| | Mean | P10 | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|
| Observable risk (%) | 0.62 | 0.07 | 0.13 | 0.30 | 0.70 | 1.48 |
| Credit score | 748.19 | 683.00 | 717.00 | 757.00 | 785.00 | 801.00 |
| Loan-to-value (%) | 76.84 | 51.00 | 68.00 | 80.00 | 90.00 | 95.00 |
| Debt-to-income (%) | 34.25 | 21.04 | 27.37 | 35.17 | 41.83 | 45.12 |

(c) Fintechs

| | Mean | P10 | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|
| Observable risk (%) | 0.63 | 0.07 | 0.13 | 0.30 | 0.70 | 1.60 |
| Credit score | 746.94 | 680.00 | 714.00 | 756.00 | 786.00 | 802.00 |
| Loan-to-value (%) | 75.50 | 51.00 | 66.00 | 80.00 | 90.00 | 95.00 |
| Debt-to-income (%) | 34.07 | 20.83 | 26.98 | 34.76 | 41.76 | 45.60 |

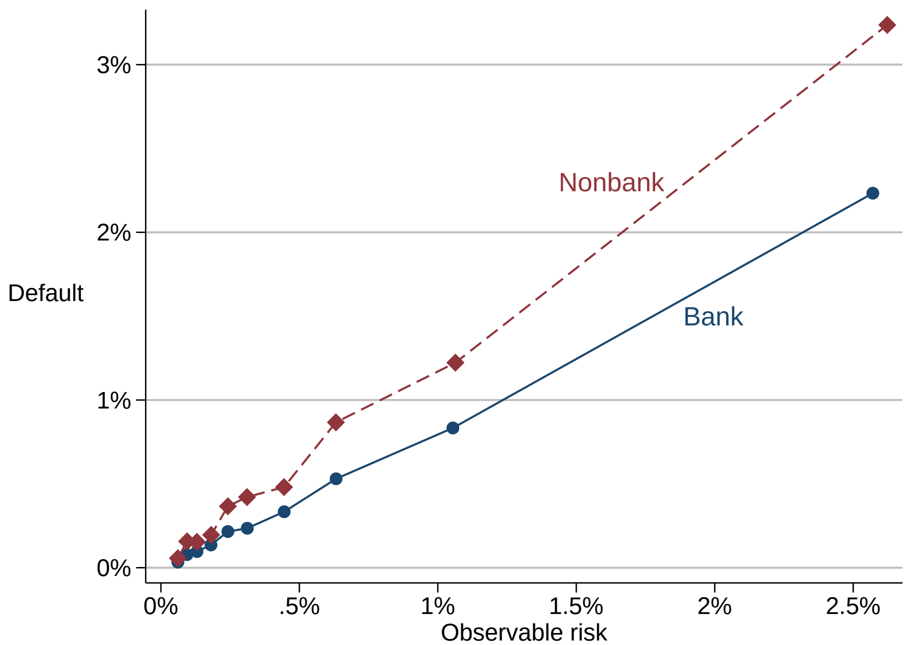
Note: These tables present summary statistics for observable risk characteristics (credit score, loan-to-value ratio (%), debt-to-income ratio (%), and observable risk) for banks, nonbank-nonfintechs, and fintechs. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

### 2.4.2 Observation 6: nonbanks exhibit more defaults conditional on observable risk

Figure 4 shows that nonbanks are associated with greater default rates conditional on observable risk. Similarly, Table 5 column (1) shows that nonbanks are associated with higher default rates, column (2) shows that this relationship continues to hold even after controlling for observable risk, column (3) shows that it continues to hold after controlling for a similar set of additional observable characteristics as in column (3) of Table 2, and column (4) shows that it continues to hold after additionally controlling for the interest rate net of the total g-fee. Based on the estimate in column (2), nonbanks are associated with a 19 basis point increase in the default rate conditional on observable risk, which corresponds to 43% of the 44 basis point default rate of banks. Table D.10 in Internet

Figure 4: Default, observable risk, and lender type

This figure presents a binned scatterplot of the default rate on observable risk for banks and nonbanks. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.




Appendix D.7 shows that the results are similar when comparing banks to either fintechs or nonbank-nonfintechs.[21]

### 2.4.3 Observation 7: nonbanks exhibit higher interest rates conditional on observable risk

Figure 5 shows that nonbanks are associated with higher interest rates net of g-fees conditional on observable risk, consistent with their riskier credit profiles (Observation 6). Similarly, Table 6 column (1) shows that nonbanks are associated with higher interest

[21] Observation 6 updates previous work indicating that, in the context of loans securitized by the GSEs, the association between nonbanks and default 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. Table D.11 shows that the association between nonbanks and defaults has become more positive over time. While explaining this change over time is not the focus of the paper, one brief speculation is that as nonbanks have taken over greater market share from banks, they may have a relatively greater incentive to lend to riskier borrowers in order to continue expanding their business.

Table 5: Default, observable risk, and lender type

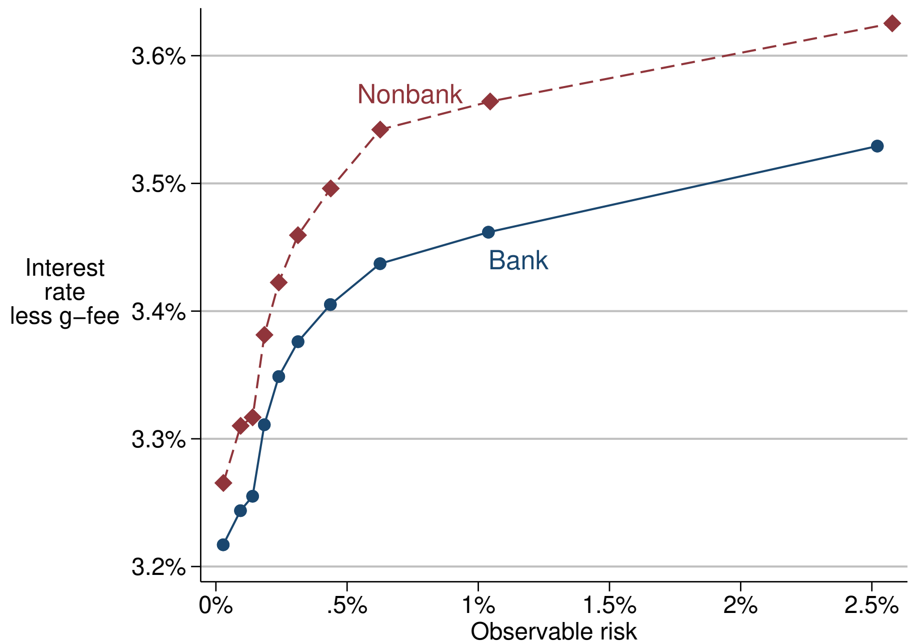
| | (1) Baseline | (2) Obs. risk | (3) Controls | (4) + IR |
|---|---|---|---|---|
| Nonbank | 0.268*** | 0.187*** | 0.174*** | 0.153*** |
| | (23.67) | (16.66) | (15.55) | (13.26) |
| Observable risk | | 0.954*** | | |
| | | (66.73) | | |
| IR - g-fee | | | | 0.315*** |
| | | | | (6.91) |
| Observations | 2,109,041 | 2,109,041 | 2,109,029 | 2,109,029 |
| $R^2$ | 0.091 | 0.100 | 0.103 | 0.103 |
| ZIP × Year-quarter FE | Yes | Yes | Yes | Yes |
| Controls | No | No | Yes | Yes |

Note: Column (1) regresses an indicator for default (multiplied by 100) on an indicator for nonbanks while controlling for ZIP code by year-quarter fixed effects. Column (2) adds observable risk as a regressor. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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 absorbs observable risk); income decile indicators; family type indicators (i.e. single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; term indicators; appraisal value decile indicators; an indicator for a loan having an interest-only period; an indicator for a refinance loan; loan amount decile indicators; an indicator for self-employed borrowers; an indicator for first-time homebuyers; an indicator for full income documentation; and an indicator for full asset documentation. Column (4) additionally adds 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

rates, column (2) shows that this relationship continues to hold even after controlling for the g-fee, and column (3) shows that it continues to hold after controlling for a similar set of additional observable characteristics as in column (3) of Table 2. Based on the estimate in column (2), nonbanks are associated with an 8 basis point increase in the interest rate conditional on observable risk, which corresponds to around 18% of a standard deviation. Table D.12 in Internet Appendix D.8 shows that the results are similar when comparing banks to either fintechs or nonbank-nonfintechs.

Figure 5: Interest rates, observable risk, and lender type

This figure presents a binned scatterplot of the interest rate net of the total g-fee on observable risk for banks and nonbanks while controlling for year-month fixed effects. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.




### 2.4.4 Observation 8: the presence of fintechs is associated with relatively lower interest rates and default rates by banks

Table 7 examines interactions between banks and nonbanks by showing how the differences between them varies with the presence of fintechs, which have disproportionately contributed to the increasing market share of nonbanks, over the period 2011-2017. Note that for this time period 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.

Similar to Table 5, column (1) shows that banks are associated with lower default rates during this longer time period. Column (2), which adds the interaction of the bank indicator with the share of origination volume in a county in the last year attributable to fintechs (scaled from 0 to 1), shows that the difference between banks and nonbanks

Table 6: Interest rates, observable risk, and lender type

| | (1)<br>Baseline | (2)<br>Obs. risk | (3)<br>Controls |
|---|---|---|---|
| Nonbank | 0.085*** | 0.077*** | 0.066*** |
| | (163.73) | (151.88) | (155.16) |
| Observable risk | | 0.094*** | |
| | | (328.55) | |
| Observations | 2,109,041 | 2,109,041 | 2,109,029 |
| $R^2$ | 0.448 | 0.476 | 0.656 |
| ZIP × Year-quarter FE | Yes | Yes | Yes |
| Controls | No | No | Yes |

Note: Column (1) regresses the interest rate net of the total g-fee on an indicator for nonbanks while controlling for ZIP code by year-quarter fixed effects. Column (2) adds observable risk as a regressor. Observable risk is the estimated probability of default based on credit score, the loan-to-value ratio, and the 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 absorbs observable risk); income decile indicators; family type indicators (i.e. single female, single male, or more than 1 borrower); indicators for Black and Hispanic borrowers; term indicators; appraisal value decile indicators; an indicator for a loan having an interest-only period; an indicator for a refinance loan; loan amount decile indicators; an indicator for self-employed borrowers; an indicator for first-time homebuyers; an indicator for full income documentation; and an indicator for full asset documentation. Column (4) additionally adds 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, 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 where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

widens as fintechs occupy a greater market share. Similar to Table 6, column (3) shows that banks are associated with lower interest rates, while column (4) shows that the difference between banks and nonbanks widens as fintechs occupy a greater market share. Similarly, Figure D.5 in Internet Appendix D.9 shows that nonbanks exhibited a relative increase in default rates and interest rates compared to banks during this period, which was relatively more pronounced in counties with a greater presence of fintechs in 2017. These results are consistent with nonbanks competing more aggressively for the riskier borrowers for a given level of observable risk, resulting in banks focusing on relatively safer borrowers.

### 2.4.5 Observations 5-8 interpretation

Section 3 rationalizes Observations 5-8 with a model in which nonbank lenders have a lower loss expected given default, which gives them a greater incentive to lend to borrow-

Table 7: Interest rates, default, observable risk, lender type, and fintech market share

| | (1) Default | (2) Default | (3) IR | (4) IR |
|---|---|---|---|---|
| Bank | -0.129*** | -0.077*** | -0.078*** | -0.073*** |
| | (-22.34) | (-5.72) | (-250.97) | (-98.10) |
| Obs. risk | 1.028*** | 1.027*** | 0.180*** | 0.180*** |
| | (146.99) | (146.96) | (947.05) | (946.83) |
| Lag fintech share × Bank | | -0.531*** | | -0.047*** |
| | | (-4.06) | | (-6.72) |
| Observations | 8,678,978 | 8,678,960 | 8,678,978 | 8,678,960 |
| $R^2$ | 0.030 | 0.030 | 0.453 | 0.453 |
| County × Year-quarter FE | Yes | Yes | Yes | Yes |
| Controls | No | No | No | No |

Note: Column (1) regresses an indicator for default (multiplied by 100) on an indicator for banks while controlling for observable risk and county by year-quarter fixed effects. Column (2) adds the interaction of the bank indicator with the share of origination volume in a county in the last year attributable to fintechs (scaled from 0 to 1). Column (3) and column (4) are similar to column (1) and column (2) except using the interest rate 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), 2011-2017, restricting to fixed rate, 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, and loans with subordinate financing.

ers with greater observable and unobservable risk while also collecting a higher interest rate and causing rival lenders to shift to safer borrowers with lower interest rates. 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.

# 3 Model

The preceding section provides evidence that lenders price for credit risk in a manner indicative of performing additional screening relative to the GSEs' g-fees. This section develops a model of mortgage lender competition which is consistent with these observations and which additionally shows that lender overlays can lead to either higher or lower interest rates, depending on a borrower's observable risk, compared to a counterfactual in which the discretionary behavior of lenders is eliminated. We also use the model to show 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.

### 3.1 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 $\theta$ of consumers: type $d$ consumers default, while type $r$ consumers repay the loan.[22] 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 $\lambda_r = 1 - \lambda_d$.

### 3.2 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.

An elaboration of the model follows in approximately backward order.

### 3.3 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 borrower.

[22]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.

### 3.3.1 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.[23] For simplicity, we focus on a symmetric equilibrium in which all lenders have the same information level $\psi$. See Section 5 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[24]

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

$$f(s|r;\psi) = \left(1 + \left(s - \frac{1}{2}\right)\frac{\psi}{\lambda_r}\right) \tag{3}$$

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 $\psi$ increases.

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

$$\begin{aligned} D(s;\psi) &\equiv Pr(d|s;\psi) \\ &= \lambda_d + \left(\frac{1}{2} - s\right)\psi \end{aligned} \tag{4}$$

The properties of the posterior risk are represented graphically in Figure A.1. The posterior risk is decreasing in the signal and equal to the prior $\lambda_d$ 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.

[INSERT FIGURE A.1 HERE]

[23] Note that the information level is bounded to ensure that the signal distributions described in (2) and (3) are nonnegative.

[24] Up to a first order approximation in $\psi$, this distribution system can be assumed without loss of generality conditional on the following set of intuitive properties: the predictive distribution does not depend on the information level, the conditional distributions converge to the predictive distribution when the information level is equal to zero, and the first order effect of information on the conditional pdf for a good signal is given by the probability of receiving as high a signal under the predictive distribution. See Internet Appendix E.1 for details.

#### 3.3.2 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.[25] 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.[26] 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.[27] 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 $j$th 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 $t$:[28]

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

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

[25] 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 borrower'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).

[26] 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.

[27] See Appendix C.1 for a proof in this environment.

[28] See Appendix C.2 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,[29] which can be expressed as

$$D(s,s;\psi,n) = \lambda_d + \frac{1}{2}(n - (n+2)s)\psi \tag{6}$$

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.

## 3.4 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 $\rho$. 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

$$(1+R) - \omega D - (1+\rho) = R - (\omega D + \rho) \tag{7}$$

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

$$\underline{R}(D) = \omega D + \rho \tag{8}$$

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 (6)).[30]

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

$$\underline{R}(D(s,s;\psi,n)) = \omega\left[\lambda_d + \frac{1}{2}(n - (n+2)s)\psi\right] + \rho \tag{9}$$

If only one lender has a sufficiently optimistic signal to offer a loan, then it fully appropriates any potential surplus by charging an interest rate that is equal to the con-

[29] 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 borrowers' default risk and vanishes in the limiting case where the estimated default risk of the two lenders is the same.

[30] See Appendix C.1 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.

sumer'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.[31]

### 3.5 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 $s \geq \underline{s}$.[32,33]

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

$$\underline{s} = \frac{n}{n+1} + \frac{2(\omega\lambda_d + \rho - A)}{(n+1)\omega\psi} \tag{10}$$

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

### 3.6 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 borrowers) is given by

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

[31]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.

[32]See Appendix C.3 for a calculation.

[33]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 borrowers receiving credit that default:

$$\frac{\lambda_d Pr(s_{n:n} > \underline{s}|d;\psi)}{\lambda_d Pr(s_{n:n} > \underline{s}|d;\psi) + \lambda_r Pr(s_{n:n} > \underline{s}|r;\psi)}. \tag{12}$$

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

$$\begin{aligned} R_{exp} = \lambda_d E_{s_{n-1:n}} &\left[\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) 1_{\{s_{n-1:n} \geq \underline{s}\}} |d;\psi\right] \\ &+ \lambda_r E_{s_{n-1:n}} \left[\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) 1_{\{s_{n-1:n} \geq \underline{s}\}} |r;\psi\right]. \end{aligned} \tag{13}$$

## 3.7 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

$$\begin{aligned} \pi_L = &E_{s, s_{n-1:n}} \left[ \underbrace{(A - \underline{R}(D(s, s_{n-1:n}; \psi, n)))}_{= R - \underline{R} \text{ as in (7), with no competing lenders}} 1_{\{s = s_{n:n} \geq \underline{s}, s_{n-1:n} \leq \underline{s}\}} \right] \\ &+ E_{s, s_{n-1:n}} \left[ \underbrace{(\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)) - \underline{R}(D(s, s_{n-1:n}; \psi, n)))}_{= R - \underline{R} \text{ as in (7), with competing lenders}} 1_{\{s = s_{n:n} \geq \underline{s}, s_{n-1:n} \geq \underline{s}\}} \right] \\ &- \mu \frac{(\psi - z)^2}{2}, \end{aligned} \tag{14}$$

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.[34]

[34]See Internet Appendix E.2 for a calculation lender profits.

# 4 Comparing active and passive intermediation

## 4.1 Definitions

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 GSE 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.[35] 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 borrower'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 components can be written as follows:

$$\begin{aligned} R_{exp} = \quad & \underbrace{n\mu\frac{(\psi - z)^2}{2}}_{\text{total information cost}} \\ & + \underbrace{E_{s_{n:n}, s_{n-1:n}}[\underline{R}(D(s_{n:n}, s_{n-1:n}; \psi, n))]}_{\text{origination cost}} \\ & + \underbrace{R_{exp} - \left(n\mu\frac{(\psi - z)^2}{2} + E_{s_{n:n}, s_{n-1:n}}[\underline{R}(D(s_{n:n}, s_{n-1:n}; \psi, n))]\right)}_{\text{markup}} \end{aligned} \tag{15}$$

On the one hand, active intermediaries may exhibit lower origination costs since they lend to borrowers that are more likely to repay. On the other hand, active intermediaries

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

also have information acquisition costs and an opportunity to charge a markup, i.e.

$$R_{exp} - \underline{R}(\lambda_d) = \underbrace{\text{origination cost} - \underline{R}(\lambda_d)}_{\leq 0} + \underbrace{\text{information cost} + \text{markup}}_{\geq 0} \quad (16)$$

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:[36]

$$\begin{aligned}\pi_C = \; & \underbrace{0 * E_{s_{n:n}, s_{n-1:n}}\left[1_{\{s_{n:n} \leq \underline{s}\}}\right]}_{\text{no consumer surplus when zero willing lenders}} \\ + \; & \underbrace{E_{s_{n:n}, s_{n-1:n}}\left[(A - A) 1_{\{s_{n:n} \geq \underline{s} \geq s_{n-1:n}\}}\right]}_{\text{no consumer surplus when only 1 willing lender}} \\ + \; & \underbrace{E_{s_{n,n}, s_{n-1:n}}\left[(A - \underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n))) 1_{\{s_{n-1:n} \geq \underline{s}\}}\right]}_{\text{generally positive surplus when at least 2 willing lenders}}\end{aligned} \quad (17)$$

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

$$S = n\pi_L + \pi_C \quad (18)$$

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 (14) and (17). To compare the surplus in active and passive intermediation, it is helpful to observe that the former can be simplified

[36] See Internet Appendix E.3 for a calculation of consumer surplus.

as

$$S^{\text{active}} = E_{s_{n:n}, s_{n-1:n}} \left[ \left( A - \underbrace{\underline{R}(D(s_{n:n}, s_{n-1:n}; \psi, n))}_{\text{origination cost}} \right) 1_{\{s_{n:n} \geq \underline{s}\}} \right] - n\mu \frac{(\psi - z)^2}{2}. \tag{19}$$

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

$$S^{\text{active}} - S^{\text{passive}} = \underbrace{E_{s_{n:n}, s_{n-1:n}} \left[ \left( \underline{R}(\lambda_d) - \text{origination cost} \right) 1_{\{s_{n:n} \geq \underline{s}\}} \right]}_{\geq 0 \text{ superior screening}} \underbrace{- n\mu \frac{(\psi - z)^2}{2}}_{\leq 0 \text{ info. cost}}, \tag{20}$$

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

## 4.2 Model simulation

In our simulations, we focus on how model outcomes vary with $\lambda_d$. We therefore normalize the cost of funding $\rho$ 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 select fixed values for the other parameters ($n$, $A$, $\omega$, $\mu$) based on the following considerations.

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)).

The remaining parameters ($A$, $\omega$, $\mu$) are selected to match the intensive and extensive margins of overlays. In particular, they are estimated by minimizing the precision-weighted sum of squared deviations between the model and empirical counterparts for the following three characteristics:[37]

1. The intensive margin of overlays is represented by column (3) of Table 1, which shows that an increase in observable risk by 1 percentage point is on average associated with a .094 percent increase in interest rates net of g-fees. Note that we determine the model analog by computing the average interest rate (over repaying and defaulting borrowers) for each level of observable risk and then taking a weighted average over observable risk based on the empirical distribution.

[37] Specifically, the weight for a given characteristic is the squared inverse of the corresponding standard error.

2. The extensive margin of overlays is represented by Figure 3, which shows the rejection rate of applications accepted by the GSEs. We select the parameters to match the average acceptance rate of .965.

3. We also match the average slope of the acceptance rate with respect to observable risk based on a simple linear regression of an indicator for acceptance on observable risk and a constant term. The average slope is estimated to be -.015 per percentage point of observable risk. Again, we compute the model analog by weighting over observable risk based on the empirical distribution.

Table B.1 presents the selected parameters, while Table B.2 compares the empirical and model-generated values of the matched characteristics.

[INSERT TABLE B.1 HERE]

[INSERT TABLE B.2 HERE]

Figure 6 compares active and passive intermediation for varying degrees of $\lambda_d$. 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 borrower to determine the interest rate, and disparities in the assessment of the borrower'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 borrower risk increases.[38]

For sufficiently high $\lambda_d$, active intermediaries start to reject applications, resulting in a reduction of the default rate compared to passive intermediation.[39] 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 $\lambda_d$ 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 $\lambda_d$ becomes too high, then lenders lose

[38] See Figure F.1 in Internet Appendix F for the direct association between interest rates and default as functions of $\lambda_d$.

[39] See Figure F.2 in Internet Appendix F for a more detailed decomposition of the number of offers received by a borrower as a function of $\lambda_d$.

the incentive to invest in screening technology at all, causing them to leave the market. However, for borrowers with high observable risk, active intermediaries are more likely to offer lower interest rates or lend at all compared to passive intermediaries.

Figure 7 compares the total surplus generated by active and passive intermediation, Active intermediation has a slightly lower total surplus for low to intermediate levels of $\lambda_d$. In this region, lenders have an incentive to acquire information in order to obtain markups, but the rate at which they screen out risky borrowers is relatively limited compared to the acquisition cost. For higher levels of $\lambda_d$, information acquisition leads lenders to more substantively reduce origination costs, in which case the benefit of superior screening outweighs the acquisition cost.

Figure A.2 illustrates the role of the lender's loss given default $\omega$ in determining overlays. As $\omega$ increases, lenders deny more applications and have lower default rates. They also charge higher interest rates, which is partly driven by the direct effect of $\omega$ on origination costs and partly driven by the fact that lenders can charge higher markups since there is less often competition from rival lenders, as shown in Figure F.3 in Internet Appendix F.

[INSERT FIGURE A.2 HERE]

Finally, Figure A.3 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. Therefore, increasing competition is more likely to lead to lower interest rates in the safer segments of the market where the markup occupies a greater share of the interest rate, but it is also more likely to lead to higher interest rates in the risky segments of the market where the origination cost occupies a greater share of the interest rate. This result is consistent with Yannelis and Zhang (2021), who provide evidence of a similar effect of competition in the context of auto loans. To summarize, stronger competition tends to reduce the differences between active and passive intermediation, and in fact active intermediation converges to passive intermediation as $n$ increases.

[INSERT FIGURE A.3 HERE]

# 5 Heterogeneous lenders

This section presents versions of the model with heterogeneous lenders. We find that the observed differences between banks and nonbanks are more consistent with differences in the implied loss given default $\omega$ than screening quality $\psi$.

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 AUS are originated and the interest rate is determined by a zero-profits condition) for various levels of $\lambda_d$. 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 borrowers. 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 $\psi$ 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: $\rho = 0$, $n = 2$, $A = .0027$, $\omega = .066$, $\mu = .1$.

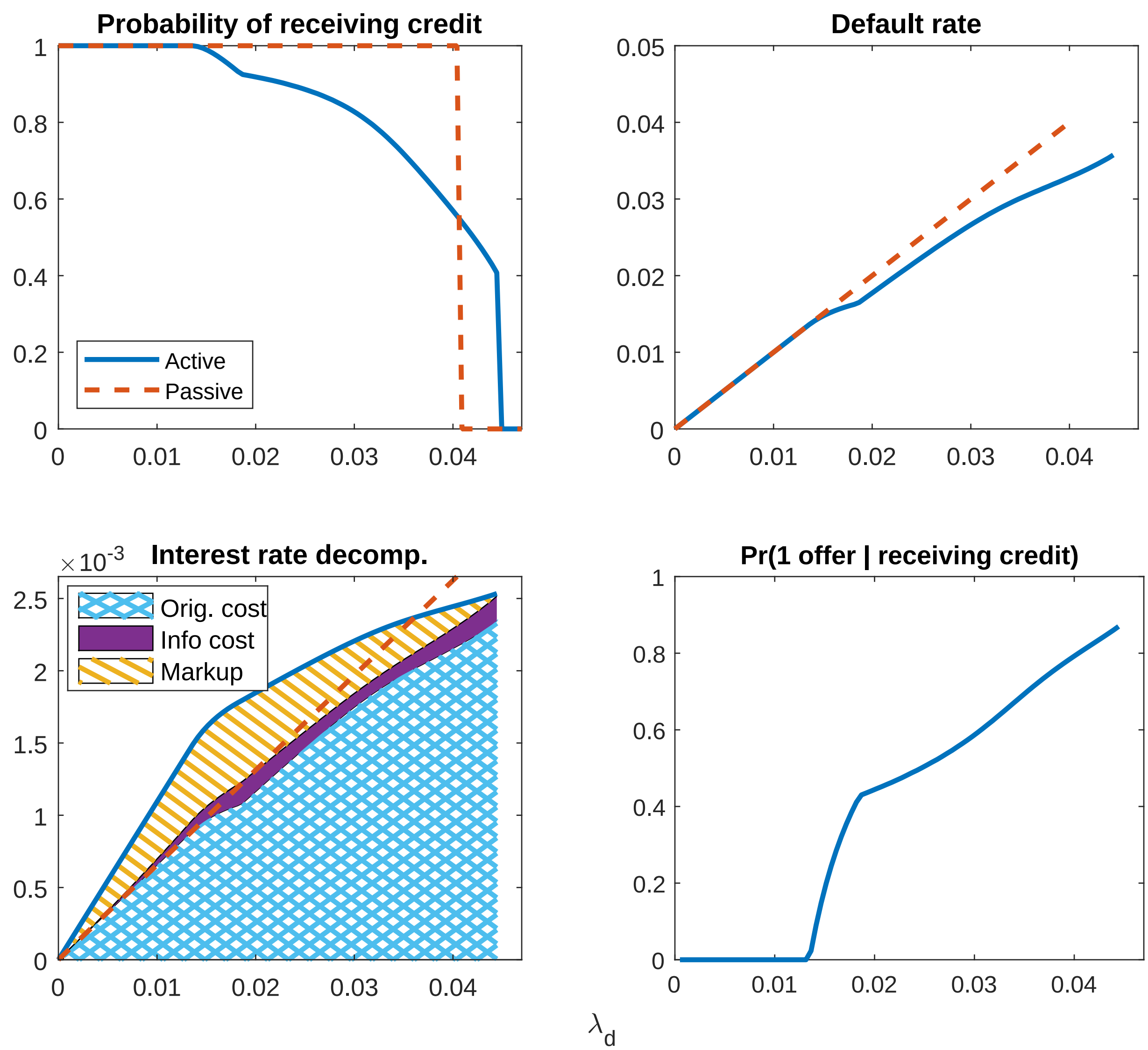
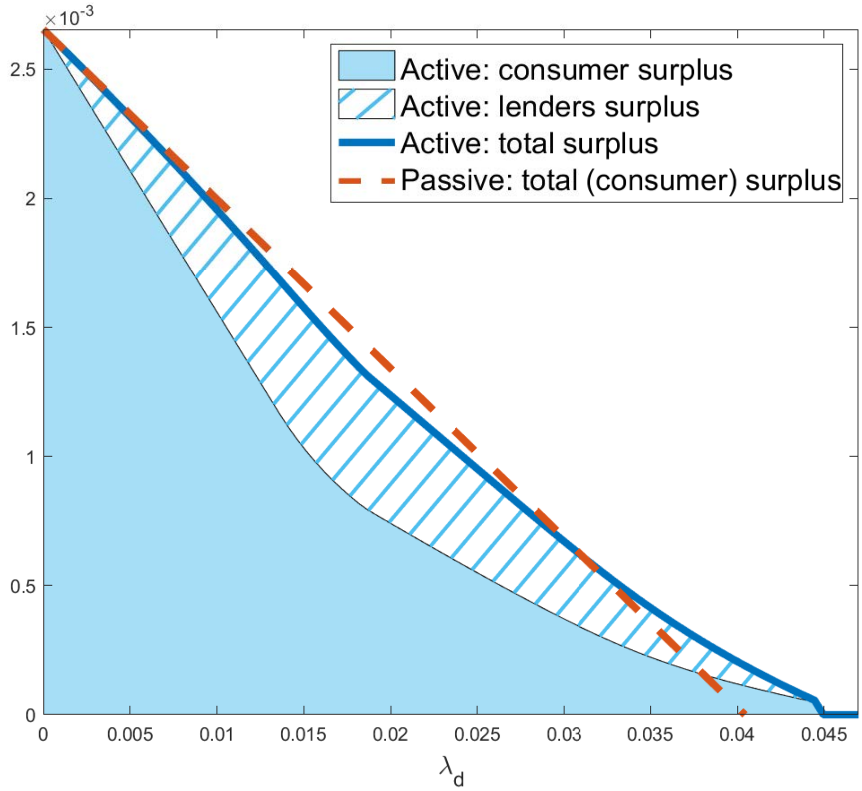


Figure 7: Surplus decomposition

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 $\lambda_d$. 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: $\rho = 0$, $n = 2$, $A = .0027$, $\omega = .066$, $\mu = .1$.




## 5.1 Heterogeneous $\psi$

For simplicity, we assume that there are only 2 lenders with exogenous information levels $\psi_1$ 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 original model in Section 3.

The posterior risk of default conditional on receiving signal $s_i$ with information level $\psi_i$ is directly analogous to equation (4) and can be expressed as

$$D(s_i;\psi_i) \equiv Pr(d|s_i;\psi_i) = \lambda_d + \left(\frac{1}{2} - s_i\right)\psi_i \tag{21}$$

The posterior risk conditional on the lender's own signal and inferring from the equilibrium interest rate the signal of the competing lender becomes[40]

$$D(s_1,s_2;\psi_1,\psi_2) \equiv Pr(d|s_1,s_2;\psi_1,\psi_2)$$
$$\underset{\psi\approx 0}{\approx} \lambda_d + \left(\frac{1}{2} - s_1\right)\psi_1 + \left(\frac{1}{2} - s_2\right)\psi_2 \tag{22}$$

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.[41] 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[42]

$$D(s_i,s_i;\psi_i,\psi_i) = \lambda_d + (1 - 2s_i)\,\psi_i \tag{23}$$

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 (23)).[43]

**Proposition 3.** *A lender's interest rate offer is equal to*

$$\underline{R}(D(s_i,s_i;\psi_i,\psi_i)) = \omega\,[\lambda_d + (1 - 2s_i)\,\psi_i] + \rho \tag{24}$$

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.[44]

[40]See Section C.4 for a calculation.

[41]See Appendix C.5 for a proof.

[42]Recall from equation (28) 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 (22) obtains equation (23).

[43]See Appendix C.5 for a proof.

[44]See Appendix C.6 for a proof.

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

$$\underline{s}_i = \frac{2}{3}\left[\frac{\psi_1+\psi_2}{2\psi_i} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_i}\right] \tag{25}$$

*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*

$$\underline{s}_i = \frac{1}{2} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_i} \tag{26}$$

Figure A.4 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 $\lambda_d$.[45] The more informed lender is associated with a greater willingness to provide credit, which generally becomes more pronounced for riskier borrowers.[46] 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 $\lambda_d$ borrowers but a higher interest rate for high $\lambda_d$ borrowers.[47]

[INSERT FIGURE A.4 HERE]

## 5.2 Heterogeneous $\omega$

In this section, we assume there are 2 lenders with the same exogenous $\psi$ 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 screening:[48]

$$\rho_2 = \rho_1 + \lambda_d(\omega_1 - \omega_2) \tag{27}$$

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 Section 5, we abstract from the information cost since the information level is exogenous.

[45]Note that $\lambda_d$ starts a point greater than 0 due to the constraint $\psi \leq 2\lambda_d$ as described in Section 3.3.1.

[46]See Figure G.1 in Internet Appendix G.1 for a more detailed decomposition of the number of offers received by a borrower.

[47]See also Figure G.2 in Internet Appendix G.1 for the direct association between interest rates and default as functions of $\lambda_d$.

[48]We later show in Section 5.3 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).

The posterior risk of default conditional on receiving signal $s_i$ with information level $\psi$ is directly analogous to equation (4) and can be expressed as

$$\begin{aligned} D(s_i;\psi) &\equiv Pr(d|s_i;\psi) \\ &= \lambda_d + \left(\frac{1}{2} - s_i\right)\psi \end{aligned} \tag{28}$$

The posterior risk conditional on the lender's own signal and inferring from the equilibrium interest rate the signal of the competing lender becomes[49]

$$\begin{aligned} D(s_1,s_2;\psi) &\equiv Pr(d|s_1,s_2;\psi) \\ &\underset{\psi\approx 0}{\approx} \lambda_d + (1 - s_1 - s_2)\,\psi \end{aligned} \tag{29}$$

Lender $i$'s zero-profit interest rate is then

$$\underline{R}_i(D(s_1,s_2;\psi)) = \omega_i\left[\lambda_d + (1 - s_1 - s_2)\,\psi\right] + \rho_i \tag{30}$$

In contrast to the baseline model and the version with heterogeneous $\psi$, the version with heterogeneous $\omega$ 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:

$$E_{s_{-i}}\left[\left(B_{-i}(s_{-i}) - \underline{R}_i(D(s_1,s_2;\psi))\right)1_{a_i+b_is_i<B_{-i}(s_{-i})}\right] \tag{31}$$

This determines the following equilibrium.[50]

**Proposition 5.** *There is an equilibrium in which the bidding strategies are given by*

$$B_i(s_i) = \omega_i\left[\lambda_d + \omega_i\left(\frac{1}{2} - s_i\right)\psi\right] + \rho_i \tag{32}$$

Additionally, each lender offers a loan on the condition that it will achieve non-negative 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.

[49]This follows from the proof in Appendix C.2 for the case of 2 lenders.
[50]See Appendix C.7 for a proof.

This determines the following participation threshold.[51]

**Proposition 6.** *A lender's participation threshold is equal to*

$$\underline{s}_i = \frac{2}{3}\left[1 + \frac{2\omega_{-i} - \omega_i}{\omega_1\omega_2}\frac{(\omega_i\lambda_d + \rho_i - A)}{\psi}\right] \tag{33}$$

*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*

$$\underline{s}_i = \frac{1}{2} + \frac{\omega_i\lambda_d + \rho - A}{\omega_i\psi} \tag{34}$$

Figure A.5 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 $\lambda_d$. 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 borrowers.[52] The lender with lower loss given default is also associated with a higher default rate, origination cost, and overall interest rate.[53] Figure G.6 in Internet Appendix G.2 shows how the participation thresholds $s_i$ vary with $\lambda_d$. It suggests that the lender with greater loss given default restricts to sufficiently strong borrowers, leaving many borrowers with weaker credit assessments to be serviced by the lender with lower loss given default. Figure G.5 in Internet Appendix G.2 compares the case of 2 lenders with different $\omega$ to the case of 2 homogeneous lenders with the same $\omega$.

[INSERT FIGURE A.5 HERE]

## 5.3 Comparison with empirical observations

The empirical observations comparing banks and nonbanks are most consistent with non-banks having a lower expected loss given default $\omega$:

1. The upper left subfigure of Figure A.5 shows that lenders with lower $\omega$ tend to lend relatively more to observably risky borrowers, which matches the observation that nonbanks exhibit higher observable risk (Observation 5 in Section 2.4.1).

2. The upper right subfigure of Figure A.5 shows that lenders with lower $\omega$ tend to have higher default rates conditional on observable risk, which matches the observation

[51] See Appendix C.8 for a proof.

[52] See Figure G.3 in Internet Appendix G.2 for a more detailed decomposition of the number of offers received by a borrower.

[53] See also Figure G.4 in Internet Appendix G.2 for the direct association between interest rates and default as functions of $\lambda_d$.

that nonbanks exhibit more defaults conditional on observable risk (Observation 6 in Section 2.4.2).

3. The middle left subfigure of Figure A.5 shows that lenders with lower $\omega$ tend to have a higher interest rate, which matches the observation that nonbanks exhibit higher interest rates conditional on observable risk (Observation 7 in Section 2.4.3).

By contrast, the empirical results are not consistent with banks and nonbanks having heterogeneous $\psi$. In particular, Figure A.4 shows that lenders with lower $\psi$ tend to lend relatively more to observably risk borrowers but also tend to have lower default rates conditional on observable risk, which does not fit the profile of either banks or nonbanks.

The model yields notable implications of the increasing market share of nonbanks. First, Figure G.6 in Internet Appendix G.2 shows that the presence of the low $\omega$ lender tends to induce "cream-skimming" behavior in which the high $\omega$ lender takes only the safest borrowers for a given level of observable risk, which is consistent with the results in Section 2.4.4 that a larger market share of fintechs is associated with banks having lower default rates and interest rates compared to nonbanks. Second, Figure A.2 shows that if the market eventually becomes dominated by nonbanks, then default rates will be higher.[54]

# 6 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 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 additionally shows that the discretionary behavior of lenders can lead to directionally different effects on interest rates relative to a counterfactual passive intermediation scenario for borrowers with different levels of observable risk. This is due to the counteracting effects of higher markups and lower origination costs.

[54]The implication for interest rates is less clear and depends on additional assumptions about the cost of funding $\rho$. For example, on the one hand, Figure A.2 shows that a reduction of $\omega$ with no change in $\rho$ in an environment with homogeneous lenders leads to lower interest rates due to the lower origination costs as well as more aggressive competition. On the other hand, Figure G.7 shows that if $\rho$ also adjusts to maintain a constant origination cost in the absence of screening as in equation (27), then a reduction of $\omega$ has a generally smaller effect on interest rates and can lead to slightly higher interest rates for observably risky borrowers.

We also show that nonbanks, which comprise an increasing share of the mortgage market, exhibit different intermediation patterns compared to banks, such as higher default rates conditional on observable risk, and higher interest rates compared to banks. Nonbanks also affect the intermediation activity of banks, as the growing presence of fintechs has been associated with a decrease in interest rates and default rates for banks. Through the lens of the model, the behavior of nonbanks is consistent with them 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.

From a policy perspective, these results suggest that the added value of implementing the GSE segment of the mortgage market through private intermediaries consists of decreasing the cost of housing credit for observably risky borrowers, albeit at the expense of increasing markups for the majority of borrowers. Additionally, while the increasing presence of nonbank lenders that are more associated with observably risky borrowers could further improve the access to credit, it could also lead to a riskier pool of borrowers, albeit still within the underwriting requirements of the GSEs.

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# Appendix

## A Additional figures

Figure A.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 $\psi$.

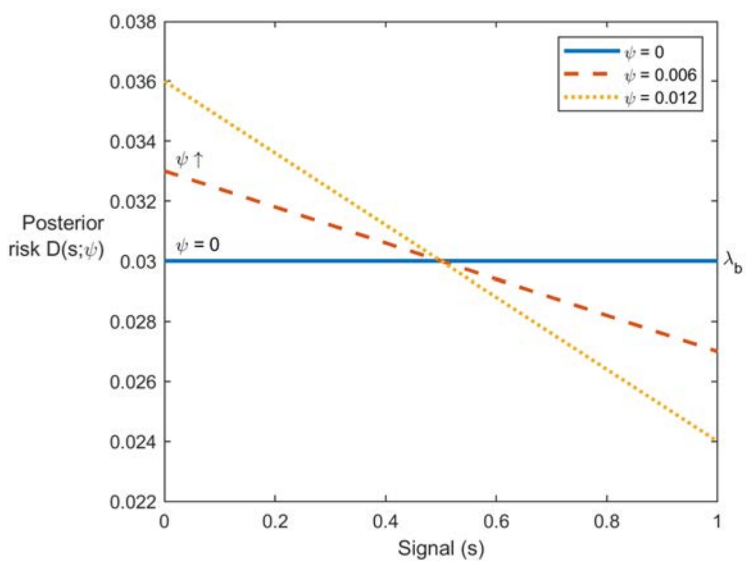


Figure A.2: Active intermediation as $\omega$ varies

These figures show various features of the model for a low loss given default $\omega$ and a high loss given default. 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 borrowers. 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 information cost* is the lenders' combined cost associated with the parameter $\psi$ corresponding to the quality of screening divided by the probability of receiving credit. The *average markup* is the lenders' combined expected profits (average interest rate - average origination cost - information cost) divided by the probability of receiving credit. Parameters: $\rho = 0$, $n = 2$, $A = .0027$, $\omega = .066$ and $.09$, $\mu = .1$.

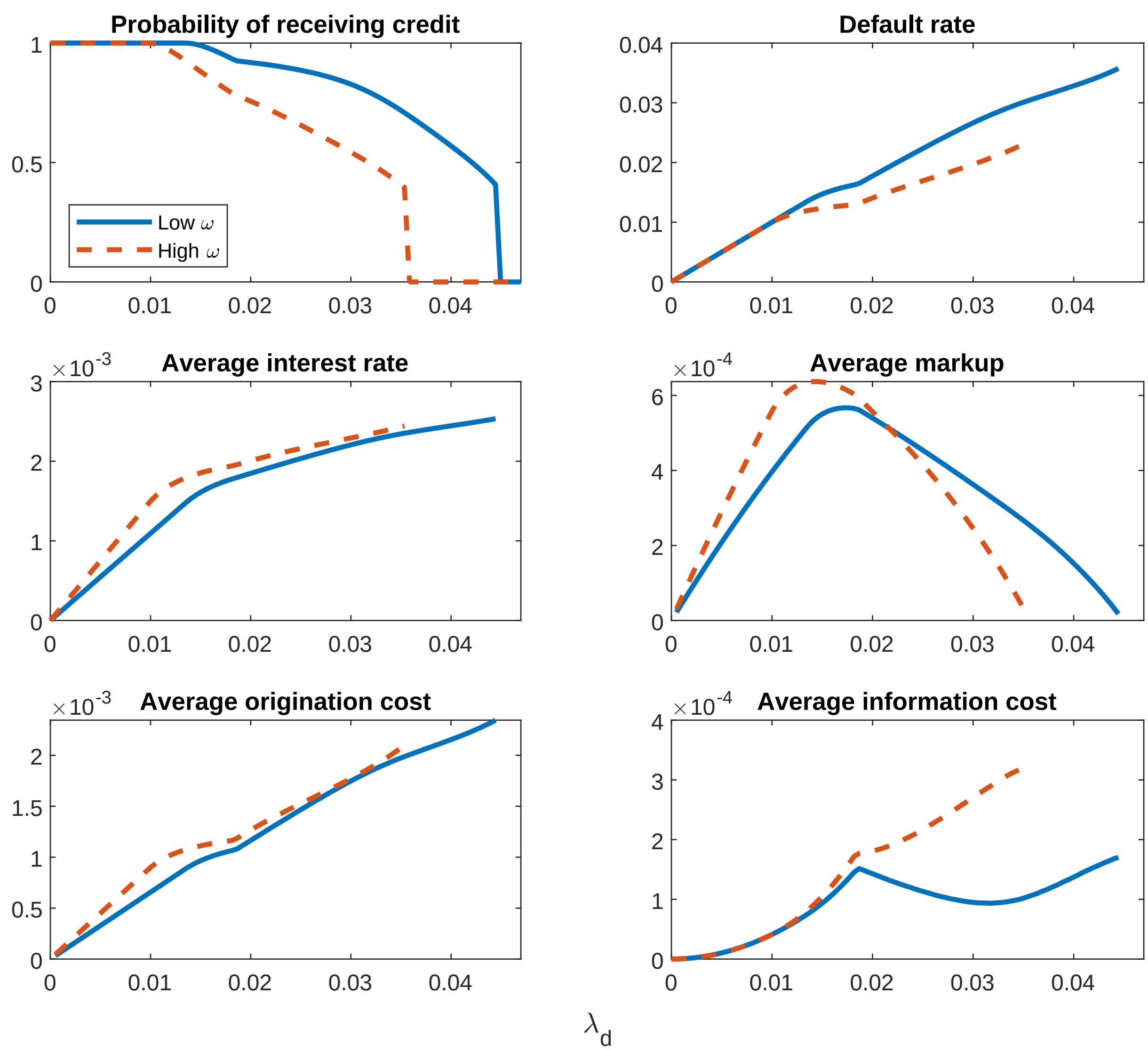


Figure A.3: Active intermediation as $n$ varies

These figures show various features of the model when the number of lenders $n$ is equal to 2 or 3. The *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 borrowers. 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 information cost* is the lenders' combined cost associated with the parameter $\psi$ corresponding to the quality of screening divided by the probability of receiving credit. The *average markup* is the lenders' combined expected profits (average interest rate - average origination cost - information cost) divided by the probability of receiving credit. Parameters: $\rho = 0$, $n = 2$ and 3, $A = .0027$, $\omega = .066$, $\mu = .1$.

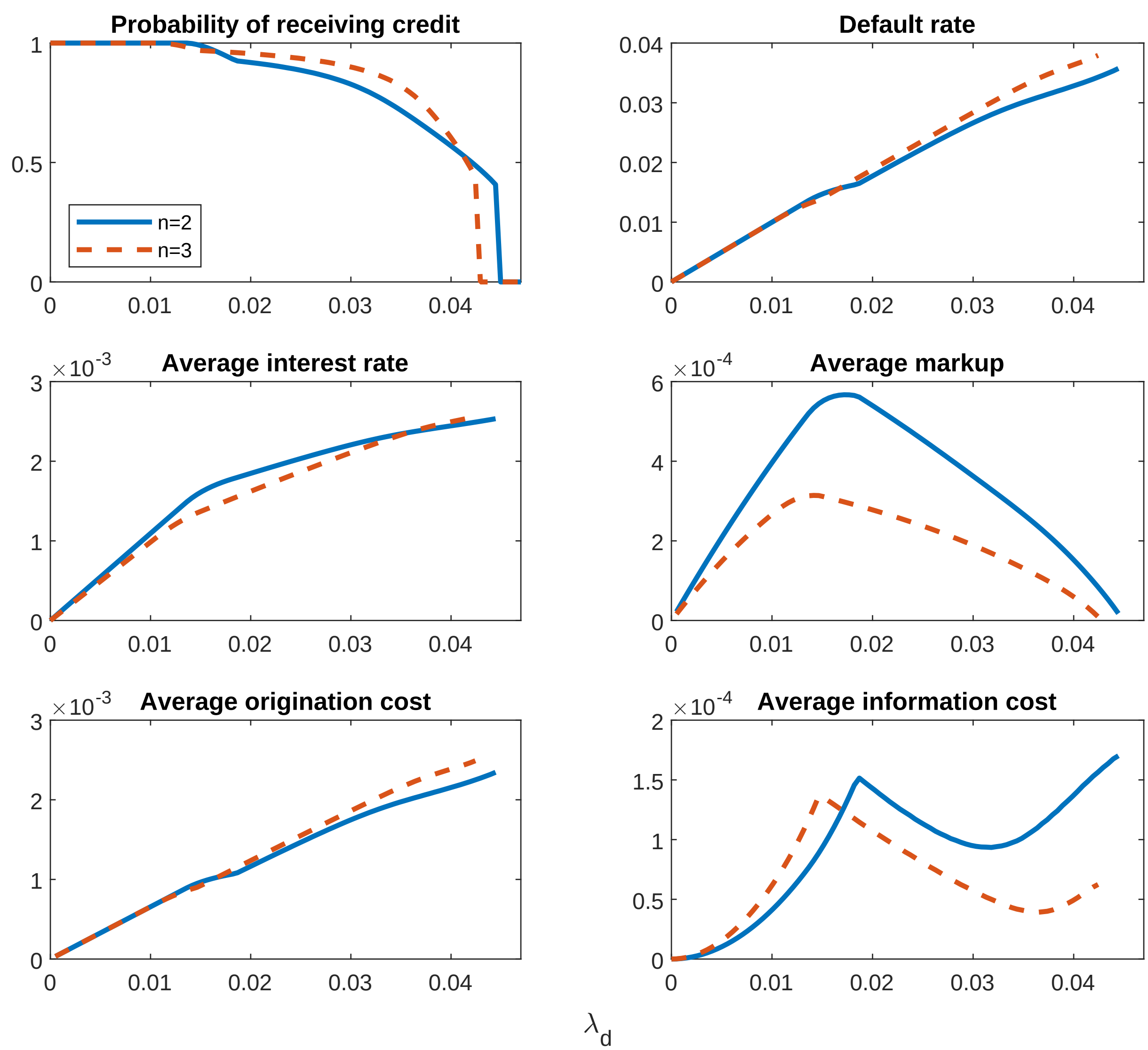


Figure A.4: Active intermediation with heterogeneous $\psi$

These figures show various features of the version of the model with 2 lenders with exogenous and different information levels $\psi$ (described in Section 5.1). 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 borrowers. 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 $.02$.

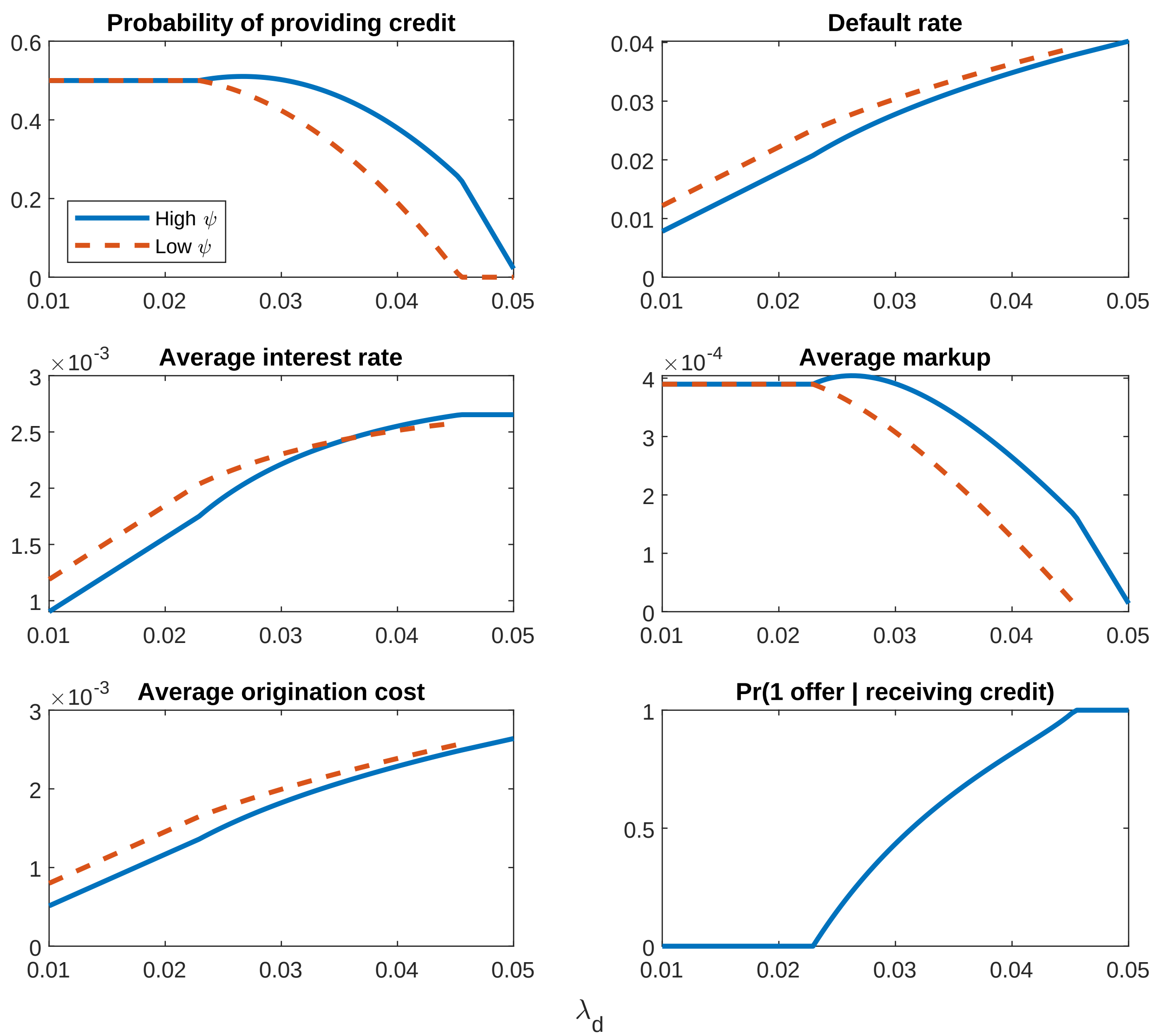
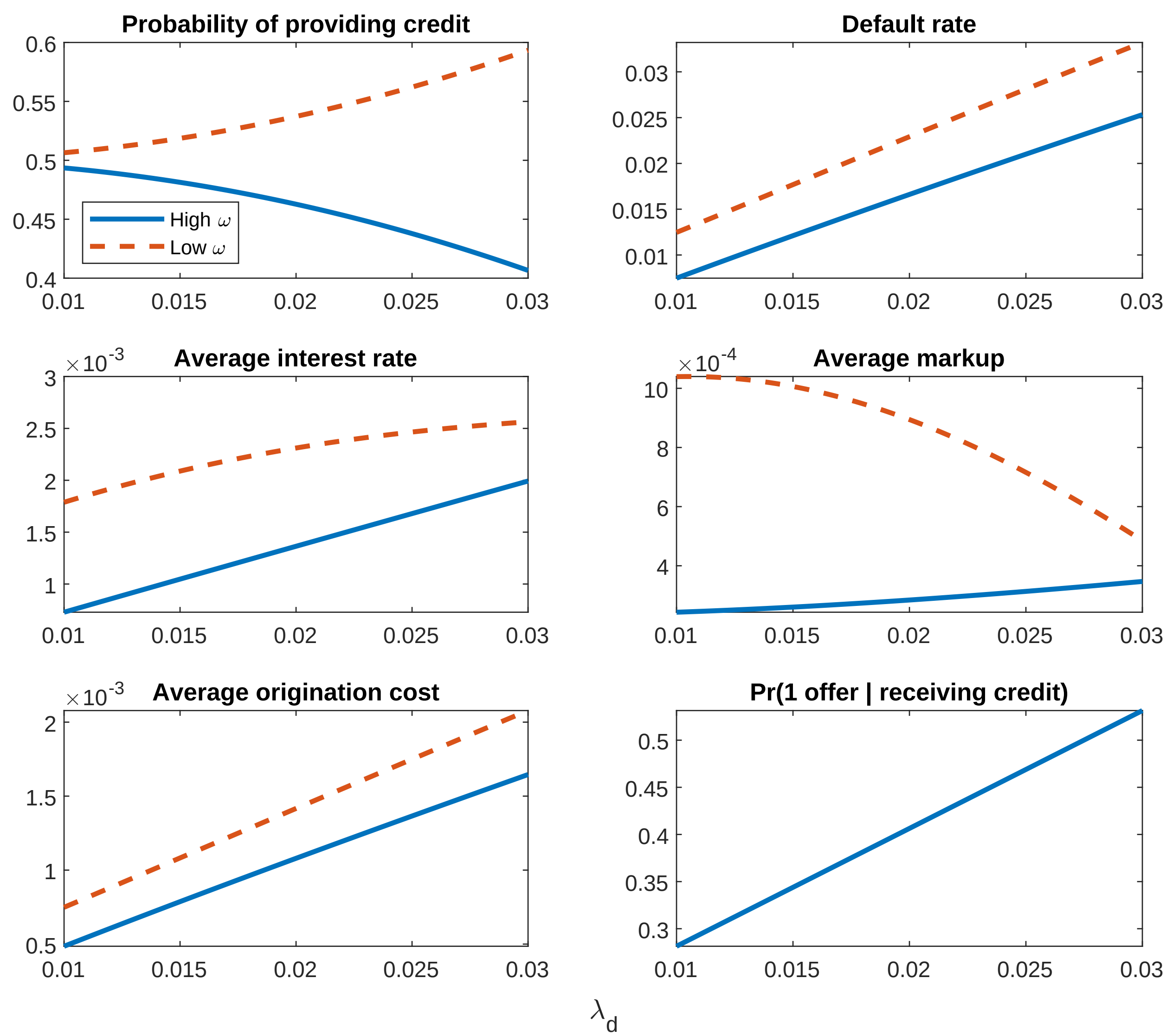


Figure A.5: Active intermediation with heterogeneous $\omega$

These figures show various features of the version of the model with 2 lenders with exogenous and the same information levels $\psi$ but different losses given default $\omega$ (described in Section 5.2). 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 borrowers. 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 $\omega$ and given by equation (27) for low $\omega$, $\mu = .01$, $\psi = .02$.



# B Additional tables

Table B.1: Selected parameters

| Parameter | Value |
|---|---|
| Lenders ($n$) | 2 |
| Borrower willingness to pay ($A$) | 0.0027 |
| Loss given default ($\omega$) | 0.0656 |
| Information cost ($\mu_b$) | 0.1028 |

Table B.2: Comparison of empirical and model-generated variables

| Variable | Empirical | Model |
|---|---|---|
| Average effect of observable risk on interest rate - g-fee | 0.094 | 0.092 |
| Average acceptance rate | 0.965 | 0.97 |
| Average effect of observable risk on acceptance rate | –0.015 | –0.018 |

# C Proofs

## C.1 Proof of Proposition 1

This section shows using an argument like the one in Milgrom (1981) 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 (8) is the zero-profits interest rate corresponding to the lender's probability of default $D$, $D(s,t;\psi,n)$ introduced in equation (5) 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 (6) 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.[55] By substituting in equation (6), 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

[55] 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.

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:

$$\underline{R}(D(s_1, s_2; \psi, n)) = \omega\left[\lambda_d + \frac{1}{2}(n - 2s_1 - ns_2)\right] + \rho. \tag{35}$$

Since lender 2's offered interest rate is higher, one can infer from equation (9) 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:

$$\underline{R}(D(s_1, s_2; \psi, n)) = \omega\left[\lambda_d + \frac{1}{2}(n - 2s_1 - ns_2)\right] + \rho. \tag{36}$$

Since lender 2's offer is lower, one can infer from equation (9) 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.

## C.2 Calculation for equation (5)

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 borrower of type $\theta$ is given by

$$f(s_{n:n} = s, s_{n-1:n} = t|\theta) = n(n-1)F(t|\theta)^{n-2}f(t|\theta)f(s|\theta) \tag{37}$$

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

$$
\begin{aligned}
f(s_{n:n}=s, s_{n-1:n}=t) &= \lambda_d f(s_{n:n}=s, s_{n-1:n}=t|d) + \lambda_r f(s_{n:n}=s, s_{n-1:n}=t|r) \\
&= \lambda_d n(n-1)F(t|d)^{n-2} f(t|d) f(s|d) + \lambda_r n(n-1)F(t|r)^{n-2} f(t|r) f(s|r) \\
&= \lambda_d n(n-1)\left(t+\frac{1}{2}\left(t-t^2\right)\frac{\psi}{\lambda_d}\right)^{n-2}\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right) \\
&\quad + \lambda_r n(n-1)\left(t+\frac{1}{2}\left(t^2-t\right)\frac{\psi}{\lambda_r}\right)^{n-2}\left(1+\left(t-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right)\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right) \\
&\underset{\psi\approx 0}{\approx} \lambda_d n(n-1)\left(t^{n-2}+(n-2)t^{n-3}\frac{1}{2}\left(t-t^2\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right) \\
&\quad + \lambda_r n(n-1)\left(t^{n-2}+(n-2)t^{n-3}\frac{1}{2}\left(t^2-t\right)\frac{\psi}{\lambda_r}\right)\left(1+\left(t-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right)\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_r}\right) \\
&\underset{\psi\approx 0}{\approx} n(n-1)t^{n-2} \qquad (38)
\end{aligned}
$$

Then, by Bayesian inference we have

$$
\begin{aligned}
D(s,t;\psi,n) &\equiv Pr(d|s_{n:n}=s, s_{n-1:n}=t) \\
&= \lambda_d \frac{f(s_{n:n}=s, s_{n-1:n}=t|d)}{f(s_{n:n}=s, s_{n-1:n}=t)} \\
&= \lambda_d \frac{n(n-1)F(t|d)^{n-2} f(t|d) f(s|d)}{n(n-1)t^{n-2}} \\
&= \lambda_d f(s|d) f(t|d;\psi)\left(\frac{F(t|d)}{t}\right)^{n-2} \\
&= \lambda_d\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+\frac{1}{2}(1-t)\frac{\psi}{\lambda_d}\right)^{n-2} \\
&\underset{\psi\approx 0}{\approx} \lambda_d\left(1+\left(\frac{1}{2}-s\right)\frac{\psi}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-t\right)\frac{\psi}{\lambda_d}\right)\left(1+(n-2)\frac{1}{2}(1-t)\frac{\psi}{\lambda_d}\right) \\
&\underset{\psi\approx 0}{\approx} \lambda_d + \frac{1}{2}(n-2s-nt)\psi \qquad (39)
\end{aligned}
$$

## C.3 Proof of Proposition 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.[56] Therefore, the supplying lender charges an interest rate $A$ and has an expected zero-profits interest rate of $E_{s_{n-1:n}}[\underline{R}(D(\underline{s}, s_{n-1:n};\psi,n))|s_{n:n}=\underline{s}]$.

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

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

$$
\begin{aligned}
E_{s_{n-1:n}}[s_{n-1:n} | s_{n:n} = \underline{s}] &= \int_0^{\underline{s}} t \left[ (n-1)\frac{t^{n-2}}{s^{n-1}} \right] dt \\
&= \frac{n-1}{n}\underline{s}
\end{aligned} \tag{40}
$$

Therefore, we have

$$
\begin{aligned}
E_{s_{n-1:n}}[\underline{R}(D(\underline{s}, s_{n-1:n}; \psi, n)) | s_{n:n} = \underline{s}] &= \omega \left[ \lambda_d + \frac{1}{2}\left(n - 2\underline{s} - nE_{s_{n-1:n}}[s_{n-1:n} | s_{n:n} = \underline{s}]\right) \right] + \rho \\
&= \omega \left[ \lambda_d + \frac{1}{2}(n - (n+1)\underline{s})\psi \right] + \rho
\end{aligned} \tag{41}
$$

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

$$
\begin{aligned}
0 &= A - E_{s_{n-1:n}}[\underline{R}(D(\underline{s}, s_{n-1:n}; \psi, n)) | s_{n:n} = \underline{s}] \\
&= A - \left[ \omega \left[ \lambda_d + \frac{1}{2}(n - (n+1)\underline{s})\psi \right] + \rho \right]
\end{aligned} \tag{42}
$$

## C.4 Calculation for equation (22)

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

$$
\begin{aligned}
f(s_1, s_2; \psi_1, \psi_2) &= \lambda_d f(s_1 | d; \psi_1) f(s_2 | d; \psi_2) + \lambda_r f(s_2 | r; \psi_1) f(s_2 | r; \psi_2) \\
&= \lambda_d \left(1 + \left(\frac{1}{2} - s_1\right)\frac{\psi_1}{\lambda_d}\right)\left(1 + \left(\frac{1}{2} - s_2\right)\frac{\psi_2}{\lambda_d}\right) \\
+ \quad & \lambda_r \left(1 + \left(s_1 - \frac{1}{2}\right)\frac{\psi_1}{\lambda_r}\right)\left(1 + \left(s_2 - \frac{1}{2}\right)\frac{\psi_2}{\lambda_r}\right) \\
&\underset{\psi \approx 0}{\approx} \lambda_d \left[1 + \left(\frac{1}{2} - s_1\right)\frac{\psi_1}{\lambda_d} + \left(\frac{1}{2} - s_2\right)\frac{\psi_2}{\lambda_d}\right] \\
&\quad + \lambda_r \left[1 + \left(s_1 - \frac{1}{2}\right)\frac{\psi_1}{\lambda_r} + \left(s_2 - \frac{1}{2}\right)\frac{\psi_2}{\lambda_r}\right] \\
&= 1
\end{aligned} \tag{43}
$$

Then, by Bayesian inference and independence we have

$$
\begin{aligned}
D(s_1,s_2;\psi_1,\psi_2) &\equiv Pr(d|s_1,s_2;\psi_1,\psi_2) \\
&= \lambda_d \frac{f(s_1,s_2|d;\psi_1,\psi_2)}{f(s_1,s_2;\psi_1,\psi_2)} \\
&= \lambda_d \frac{f(s_1|d;\psi_1)f(s_2|d;\psi_2)}{f(s_1,s_2;\psi_1,\psi_2)} \\
&= \lambda_d \left(1+\left(\frac{1}{2}-s_1\right)\frac{\psi_1}{\lambda_d}\right)\left(1+\left(\frac{1}{2}-s_2\right)\frac{\psi_2}{\lambda_d}\right) \\
&\underset{\psi\approx 0}{\approx} \lambda_d + \left(\frac{1}{2}-s_1\right)\psi_1 + \left(\frac{1}{2}-s_2\right)\psi_2
\end{aligned} \tag{44}
$$

## C.5 Proof of Proposition 3

This section shows using an argument like the one in Milgrom (1981) 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 (8) 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 (22) 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 (6) 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.[57] By substituting in equation (6), 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:

$$
\underline{R}(D(s_1,s_2;\psi_1,\psi_2)) = \omega\left[\lambda_d + \left(\frac{1}{2}-s_1\right)\psi_1 + \left(\frac{1}{2}-s_2\right)\psi_2\right] + \rho \tag{45}
$$

[57] 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.

. Since lender 2's offer is higher, one can infer from equation (24) 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 (24) 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 it doesn't observe the equilibrium interest rate.

## C.6 Proof of Proposition 4

This section shows

$$\underline{s}_i = \frac{2}{3}\left[\frac{\psi_1+\psi_2}{2\psi_i} + \frac{\omega\lambda_d+\rho-A}{\omega\psi_i}\right] \tag{46}$$

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

$$\begin{aligned} E[s_2|s_2<\underline{s}_2] &= \int_0^{\underline{s}_2} \frac{s_2}{\underline{s}_2} ds_2 \\ &= \frac{1}{2}\underline{s}_2 \end{aligned} \tag{47}$$

Therefore, we have

$$\begin{aligned} E_{s_2}[\underline{R}(D(s_1,s_2;\psi_1,\psi_2))|s_2<\underline{s}_2] &= \omega\left[\lambda_d + \left(\frac{1}{2}-\underline{s}_1\right)\psi_1 + \left(\frac{1}{2}-E_{s_2}[s_2|s_2<\underline{s}_2]\right)\right] + \rho \\ &= \omega\left[\lambda_d + \left(\frac{1}{2}-\underline{s}_1\right)\psi_1 + \left(\frac{1}{2}-\frac{1}{2}\underline{s}_2\right)\right] + \rho \end{aligned} \tag{48}$$

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

$$\begin{aligned} 0 &= A - E_{s_2}[\underline{R}(D(s_1,s_2;\psi_1,\psi_2))|s_2 < \underline{s}_2] \\ &= A - \left[\omega\left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi_1 + \left(\frac{1}{2} - \frac{1}{2}\underline{s}_2\right)\right] + \rho\right] \end{aligned} \tag{49}$$

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

$$\begin{aligned} 0 = A - \left[\omega\left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi_1\right] + \rho\right] \\ \implies \underline{s}_1 = \frac{1}{2} + \frac{\omega\lambda_d + \rho - A}{\omega\psi_1} \end{aligned} \tag{50}$$

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

## C.7 Proof of Proposition 5

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

$$E_{s_{-i}}\left[(B_{-i}(s_{-i}) - \underline{R}_i(D(s_1,s_2;\psi)))\,1_{a_i+b_is_i<B_{-i}(s_{-i})}\right] \tag{51}$$

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

$$B_i(s_i) = \omega_i\left[\lambda_d + \omega_i\left(\frac{1}{2} - s_i\right)\psi\right] + \rho_i \tag{52}$$

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 (33)) 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

$$\int_0^{\underline{s}_2} [A - [\omega_1 [\lambda_d + (1 - s_1 - s_2)\psi] + \rho_1]] ds_2 + \int_{\underline{s}_2}^{\tilde{s}_2(s_1)} [(a_2 + b_2 s_2) - [\omega_1 [\lambda_d + (1 - s_1 - s_2)\psi] + \rho_1]] ds_2 \tag{53}$$

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

$$\tilde{s}_2(s_1) = \frac{\omega_1 [\lambda_d + \psi] + \rho_1 - a_2}{b_2 + \omega_1 \psi} - \frac{\omega_1 \psi}{b_2 + \omega_1 \psi} s_1 \tag{54}$$

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

$$\begin{aligned} a_1 + b_1 s_1 &= a_2 + b_2 \tilde{s}_2(s_1) \\ &= a_2 + \frac{b_2 (\omega_1 [\lambda_d + \psi] + \rho_1 - a_2)}{b_2 + \omega_1 \psi} - \frac{b_2 \omega_1 \psi}{b_2 + \omega_1 \psi} s_1 \end{aligned} \tag{55}$$

This implies

$$\begin{aligned} b_1 &= -\frac{b_2 \omega_1 \psi}{b_2 + \omega_1 \psi} \\ &\underset{\psi \approx 0}{\approx} -\omega_1 \psi \end{aligned} \tag{56}$$

and

$$\begin{aligned} a_1 &= a_2 + \frac{b_2 (\omega_1 [\lambda_d + \psi] + \rho_1 - a_2)}{b_2 + \omega_1 \psi} \\ &\underset{\psi \approx 0}{\approx} \omega_1 \lambda_d + \omega_1 \psi + \frac{\omega_1}{b_2} (a_2 - \omega_1 \lambda - \rho_1) \\ &\underset{b_2 = -\omega_2 \psi}{=} \omega_1 \lambda_d + \omega_1 \psi - \frac{\omega_1}{\omega_2} (a_2 - \omega_1 \lambda_d - \rho_1) \\ &\underset{a_2 = \omega_2 [\lambda_d + \frac{1}{2}\psi] + \rho_2}{=} \omega_1 \left[ \lambda_d + \frac{1}{2} \psi \right] + \rho_1 \end{aligned} \tag{57}$$

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

## C.8 Proof of Proposition 6

This section shows

$$\underline{s}_i = \frac{2}{3} \left[ 1 + \frac{2\omega_i - \omega_{-i}}{\omega_1 \omega_2} \frac{(\omega_i \lambda_d + \rho_i - A)}{\psi} \right] \tag{58}$$

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

$$
\begin{aligned}
E[s_2|s_2 < \underline{s}_2] &= \int_0^{\underline{s}_2} \frac{s_2}{\underline{s}_2} ds_2 \\
&= \frac{1}{2}\underline{s}_2
\end{aligned} \tag{59}
$$

Therefore, we have

$$
\begin{aligned}
E_{s_2}[\underline{R}_1(D(s_1,s_2))|s_2 < \underline{s}_2] &= \omega_1 \left[\lambda_d + \left(1 - \underline{s}_1 - E_{s_2|s_2<\underline{s}_2}\right)\psi\right] + \rho_1 \\
&= \omega_1 \left[\lambda_d + \left(1 - \underline{s}_1 - \frac{1}{2}\underline{s}_2\right)\psi\right] + \rho_1
\end{aligned} \tag{60}
$$

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

$$
\begin{aligned}
0 &= A - E_{s_2}[\underline{R}_1(D(s_1,s_2))|s_2 < \underline{s}_2] \\
&= A - \left[\omega_1 \left[\lambda_d + \left(1 - \underline{s}_1 - \frac{1}{2}\underline{s}_2\right)\psi\right] + \rho_1\right]
\end{aligned} \tag{61}
$$

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

$$
\begin{aligned}
0 &= A - \left[\omega_1 \left[\lambda_d + \left(\frac{1}{2} - \underline{s}_1\right)\psi\right] + \rho\right] \\
\Longrightarrow \underline{s}_1 &= \frac{1}{2} + \frac{\omega_1\lambda_d + \rho - A}{\omega_1\psi}
\end{aligned} \tag{62}
$$

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