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Do intermediaries improve GSE lending? Evidence from proprietary GSE data[☆]

Joshua Bosshardt[a], Ali Kakhbod[b], Amir Kermani[b,c,*]

[a] Federal Housing Finance Agency, United States
[b] UC Berkeley Haas Business School, United States
[c] NBER, United States

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ABSTRACT

We analyze the trade-offs of having intermediaries originate government-sponsored enterprise (GSE) mortgages using proprietary GSE data. We first find evidence of lenders pricing for observable and unobservable default risk independently of the GSEs. We then develop and estimate a model of competitive lending in which lenders have skin-in-the-game and conduct additional screening beyond the GSEs' criteria. Lenders reduce costs via screening but also charge markups. On net, interest rates are higher compared to a counterfactual effectively without intermediaries. In an extension, the observed differences between banks and nonbanks are more consistent with differences in their skin-in-the-game rather than screening quality.

1. Introduction

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

Considering that the GSEs provide insurance against mortgage default risk and the progress made on the automated underwriting systems, a critical question arises: What extra value do intermediaries' discretionary overlays and pricing of mortgages offer? We specifically focus on a trade-off in which intermediaries can reduce the cost of lending by screening out borrowers who are more likely to default relative to their easily observed risk characteristics (such as credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio), but they also charge markups. We study the welfare of different types of borrowers under the current arrangement versus a counterfactual setting effectively without intermediaries.

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

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[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.

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We first provide reduced-form evidence that intermediaries price observable and unobservable risk independently of the GSEs. These facts collectively suggest that intermediaries have some skin-in-the-game and perform additional screening. However, we also find evidence of significant markups charged by the lenders. We then develop a model of competitive lending by intermediaries in which lenders perform costly screening but also have market power. We estimate the parameters based on the moments from the reduced form observations. We then use the model to study the interest rates and denial rates that different type of households would face if we changed the current system to a new one effectively without intermediaries, i.e., a system in which lending decisions are solely determined by the GSEs' underwriting criteria and competitive pricing.

As a first step to study the trade-offs of how intermediaries shape mortgage lending, we start our reduced-form analysis by showing that interest rates increase with measures of ex-ante observable default risk. We define observable risk as the probability of default predicted by a borrower's credit score, LTV ratio, and DTI ratio. We rely on variation of interest rates net of g-fees for loans offered by the same lender and within the same ZIP code and show that a one percentage point increase in observable risk is associated with a 4.2 basis point increase in interest rates net of g-fees. This result is consistent with lenders having skin-in-the-game, or a positive loss given default, due to the threat of repurchases and exclusion from the GSEs.[3] We also look at the distribution of interest rates as a function of observable risk and find that the gap between the average and the 10th percentile (or between the 90th percentile and the 10th percentile) of interest rates for the safest borrowers is 23 (49) basis points. This gap suggests that GSE intermediaries exploit significant market power. Moreover, we find that the 10th (90th) percentile increases by 1.4 (5.1) basis points for each one percentage point increase in observable risk. The difference between the slope of the average versus the 10th percentile of interest rates as a function of observable risk disciplines the parameters of the model to disentangle between lenders' skin-in-the-game and the correlation between lenders' market power and borrowers' observable risk. Although statistically significant, the association between interest rates net of g-fees and observable risk is modest in magnitude, as we determine that a 1 standard deviation increase in observable risk leads to a \$4.29 increase in monthly principal and interest rate payments for a typical loan in our sample. This result highlights that the costs associated with lenders' skin-in-the-game are small compared to the variation of interest rates within observable risk that may be due to lender markups.

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

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

For robustness, we show that the correlation between defaults and interest rates is not driven by reverse causation (i.e., the impact of interest rates on delinquencies). Specifically, we use the variation in interest rates on fixed rate mortgages caused by cross-subsidizations and discontinuities in g-fees and show that the causal impact of interest rate on delinquencies is negligible.[5]

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

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

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

[3] A "repurchase", sometimes also referred to as a "put-back", refers to when a GSE requires a lender to repurchase a loan based on charges of violating representations and warranties, which can be interpreted as errors in the underwriting process required for delivering a loan to the GSEs. The rate of repurchases increased during the financial crisis but has since remained low. Nevertheless, a 2015 survey by Fannie Mae indicates that as many as 40% lenders who deliver loans to the GSEs (or Ginnie Mae) and 60% of lenders who originate loans through wholesale channels apply overlays of some kind, citing repurchase risks and costs associated with purchasing and servicing loans that have higher default risks as the primary motivations (2015Q2 Mortgage Lender Sentiment Survey, https://www.fanniemae.com/sites/g/files/koqyhd191/files/migrated-files/resources/file/research/mlss/pdf/mlss-july2015-presentation.pdf). Additionally, Fuster et al. (2024) present evidence that lenders increased their investment in careful underwriting, consistent with increased aversion to repurchases.

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

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

We leverage the model to compare the status quo, in which lenders exercise discretionary overlays and pricing, to a counterfactual effectively without intermediaries. That is, in this counterfactual, all applications that are accepted by the GSEs' underwriting criteria are offered a loan with a zero-profits interest rate conditional on the borrower's observable risk. For example, we discuss how the counterfactual could be implemented by a combination of removing repurchase risks and standardizing mortgage applications through a platform that verifies borrowers' information, determines their eligibility for GSE loans, and disseminates the anonymous borrower information to many lenders. While the platform might still involve lenders that disburse the funds, they would have little to no ability to implement discretionary screening or pricing. The results of our estimation suggest that, absent intermediaries' screening, the amount of delinquencies would approximately triple, which would increase the marginal cost of borrowing by a similar amount on average over different levels of observable risk. However, this benefit is outweighed by the average 25 basis point markup charged by the intermediaries. Our estimations suggest that switching to the counterfactual would decrease the average interest rates for the borrowers in the bottom (top) decile of observable risk by 23 (22) basis points.

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

An extension of the model with heterogeneous lenders suggests that the observed differences between banks and nonbanks are more consistent with fundamental differences in their expected loss given default rather than either type of lender having any screening advantage. In particular, the observation that nonbanks are associated with higher observable risk and higher default rates, conditional on observable risk, is consistent with them having a lower expected loss given default. By contrast, differences in screening costs generate a smaller and opposite correlation between observable and unobservable risk. A lower loss given default and a higher screening cost both cause lenders to screen less efficiently, resulting in less informative signals about a consumer's default risk. The key difference is that a lower loss given default also allows a lender to charge a lower interest rate conditional on a given signal of a consumer's risk. The lower interest rate attracts more consumers, and this effect becomes more pronounced as observable risk increases.[6] In the model, the increasing market share of nonbanks from 2013 to 2017 can be emulated by supposing that nonbanks exhibited relative reductions in the loss given default and funding costs and became more preferred by consumers.

This paper contributes to three major themes in the literature. First, it discusses determinants and implications of access to credit in the U.S. mortgage market. This body of work encompasses, for example, lender financing (e.g., Jiang, 2023), the GSEs' automated underwriting systems (e.g., Johnson, 2022), technology (e.g., Jiang et al., 2023), regulations (e.g., DeFusco et al., 2020, Fuster et al., 2021), repurchases and servicing costs (e.g., Goodman, 2017), fair pricing and credit allocation by region (e.g., Hurst et al., 2016 and Kulkarni, 2016), and capacity constraints (e.g., Fuster et al., 2024). We contribute by providing evidence that lenders price for risk on GSE loans in a manner that is independent of the GSEs' g-fees, consistent with an intensive margin of overlays.

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

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

The rest of the paper is organized as follows. Section 2 describes the institutional background and data. Section 3 provides evidence that lenders charge risk spreads on GSE loans, consistent with an intensive margin of overlays. Section 4 develops and estimates a model in which lenders' discretionary overlays result from conducting additional screening beyond the GSEs' underwriting criteria and retaining positive losses given default. Section 5 compares the estimated model to a counterfactual effectively without intermediaries and shows that the discretionary behavior of lenders leads to higher interest rates due to substantial markups outweighing the cost-saving benefits of screening. Section 6 extends the analysis to lender types and shows that the observed differences between banks and nonbanks are more consistent with differences in their expected loss given default rather than screening quality. Section 7 concludes.

2. Institutional background and data

2.1. Institutional background

We focus on mortgage loans acquired by the GSEs. Lenders can deliver a conventional (i.e., not government insured) mortgage to the GSEs if the loan amount does not exceed the corresponding conforming loan limit value and the loan is accepted by the GSEs' automated

[6] One explanation for the difference in the expected loss given default is that banks more often have an incentive to protect rents from other business lines. By contrast, nonbanks, which typically have a monoline business model, may perceive declaring bankruptcy as a less costly limit on losses. For example, nonbanks exhibited lower rates of repurchases of risky loans they originated during the housing boom. In particular, within the set of originations from 2003 to 2008, 1.42% of the loans delivered by banks have been repurchased compared to only 0.62% of the loans delivered by nonbanks. This difference may have been due to nonbanks failing or being sold to banks during the crisis (e.g., Buchak et al., 2018) and thus not being liable to further penalties from the GSEs. Nonbanks also generally face lower regulatory scrutiny.

underwriting systems. The GSEs can purchase individual loans for cash, in which case they pool loans into mortgage-backed securities (MBS), or they can also directly swap pools of loans for mortgage-backed securities. The GSEs guarantee investors of the mortgage-backed securities against the default risk of the underlying mortgages.

As payment for the guarantee, the GSEs charge a guarantee fee or g-fee. The g-fee for a loan typically contains an ongoing component, which is charged as an annual rate, and an upfront component, which is charged as a percentage of the loan amount. The ongoing component largely depends on the loan's general product type (such as fixed rate or adjustable rate), whereas the upfront component depends more on the loan's specific risk characteristics. The upfront g-fee is the sum of components described in each GSE's respective matrix.[7] A base component for all loans with terms greater than 15 years depends on the loan-to-value (LTV) ratio and credit score.[8] Other components can depend on features of the loan (such as the loan purpose) or the property (such as the occupancy type), among other factors. Our measure of the total g-fee, expressed as an annualized rate, combines the ongoing and upfront components by converting the upfront component to an annualized rate using the loan's present value multiplier, which is estimated by the loan's guaranteeing GSE based on the expected duration of the loan.

Lenders obtain an origination revenue net of the g-fee, which can be expressed as a percentage of the loan amount. Similar to Zhang (2022), we compute origination revenue as the sum of two components: upfront closing costs and secondary marketing income. Closing costs is measured by origination charges net of lender credits, which we obtain by merging with the recently expanded HMDA data. Secondary marketing income is the present value of the deviation of a loan's interest rate net of g-fees relative to par, similar to the price of financial intermediation in Fuster et al. (2024). We compute it by subtracting the current coupon yield on GSE-guaranteed MBS[9] as of the origination date from the interest rate net of the total g-fee and multiplying by the respective present value multiplier (PVM):[10]

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

Our computation of secondary marketing income is slightly different from Fuster et al. (2024) and Zhang (2022) in that we determine the premium relative to par using the loan's guaranteeing GSE's estimated present value multiplier rather than prices in the secondary market. Despite this difference, we find similar aggregate statistics. For example, we find that the average secondary marketing income during 2018 was 3.22% (Table B.2 in Internet Appendix B), which is consistent with the finding in Fuster et al. (2024) that the price of financial intermediation averaged 1.42% during 2008–2014 while also exhibiting an average upward trend of 0.32% per year, assuming a similar trend continued from 2014 to 2018. Also, the average total origination revenue in our sample is 3.98%, which is similar to the average of 4.6% during 2018–2019 reported by Zhang (2022), especially after accounting for the fact that we additionally subtract out the upfront g-fee (which on average is equal to 0.63% in our sample).

We consider how lenders' interest rates and origination revenues vary with observable default risk as well as ex-post defaults conditional on observable risk. In the context of our analysis, default refers to a 90-day delinquency within 2 years of origination. We compute observable risk as the estimated probability of default based on easily observable characteristics, including determinants of the upfront g-fee (credit score and LTV) as well as the debt-to-income (DTI) ratio. Specifically, it is the predicted value of a regression of default (multiplied by 100) on the interaction of credit score bins corresponding to thresholds in the upfront g-fee (less than 620, 620-639, 640-659, 660-679, 680-699, 700-719, 720-739, and 740 or greater), LTV bins corresponding to thresholds in the upfront g-fee (60% or less, 60.01%–70%, 70.01%–75%, 75.01%–80%),[11] and DTI bins corresponding to quintiles.[12] When referring to the credit score for a loan, we use the representative credit score that is used to determine the g-fee. The representative credit score is the minimum of each borrower's representative score, which is either the lower score if there are two scores or the middle score if there are three.

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

2.2. Data

We use data from the Mortgage Loan Information System (MLIS), which is a proprietary regulatory dataset at the Federal Housing Finance Agency (FHFA) consisting of all loans acquired by the GSEs.[13] The aggregate results in the tables and figures of this paper do not contain any confidential or personal identifiable information.

For our baseline sample, we focus on originations during 2016–2017. We start in 2016, which is when precise data on g-fees becomes available, and we end at 2017 because we consider 2-year default rates and do not want to extend into the COVID-19 pandemic. For the results regarding origination revenue, we use the sample of originations during 2018, which we merge with the expanded HMDA data to obtain information on origination charges.[14] Note that observable risk in 2018 is computed based on the model estimated from the baseline 2016–2017 sample rather than the 2018 sample to avoid systematic changes in 2-year default rates associated with the COVID-19 pandemic.

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

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

[8] 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.

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

[10] If we split up the g-fee into the ongoing and upfront components, then this is also equivalent to: secondary marketing income = (interest rate − ongoing g-fee − MBS yield) ∗ PVM − upfront g-fee.

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

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

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

[14] 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.

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

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

3. Empirical findings

This section shows that interest rates net of g-fees are positively associated with observable risk and unobservable risk (i.e., default risk conditional on observable risk). It also shows that denials of mortgage applications increase with observable risk. These results suggest that lenders price for observable and unobservable risk independently of the GSEs, an interpretation we build upon in the following sections to analyze the costs and benefits of intermediaries for GSE loans.

3.1. Interest rates and observable risk

We start with examining the correlation between mortgage rates and observable risk. We estimate a regression of the form

$$(IR - gfee)_i = \alpha + \beta Risk_i + \delta \times X_i + \epsilon_i \tag{2}$$

where $(IR - gfee)_i$ is interest rates net of g-fees for mortgage i, $Risk_i$ is observable risk, X_i is a vector of controls (which includes ZIP code by year-quarter fixed effects, mortgage seller by year-quarter fixed effects, loan amount deciles indicators, and an indicator for full income and asset documentation in our baseline specification, while additional robustness specifications also include controls for discount points, rate lock date fixed effects, measures of consumer shopping behavior and mortgage knowledge, and measures of prepayment propensity), and ϵ_i is the error term.

We focus on the β coefficient. The null hypothesis is that lenders effectively retain no exposure to default risk and therefore, after controlling for other determinants of markups and lending cost, there is no association between interest rates (net of g-fees) and observable risk. Alternatively, if lenders have some exposure to default risk (or skin-in-the-game), such as due to the threat of put-backs and the risk of losing future business with the GSEs, then interest rates net of g-fees will be positively correlated with observable risk.

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

To illustrate the magnitude, note that in our sample the average loan amount is approximately $230,000 and the average interest rate is about 4%, resulting in a monthly principal and interest payment of $1,098 for a 30-year loan. An increase of observable risk by 1 standard deviation (about .77 percentage points) results in a 3.234 (= .77 × 4.2) basis point increase in the interest rate. This leads to a $4.29 rise in monthly principal and interest payments, which amounts to only about 0.39% of the total monthly payment. Although small in magnitude, the statistically significant positive association provides evidence that lenders internalize a cost associated with default. In our model in Section 4, this cost creates an incentive lenders engage in additional screening, which results in the observed association being smaller compared to a counterfactual without such screening.

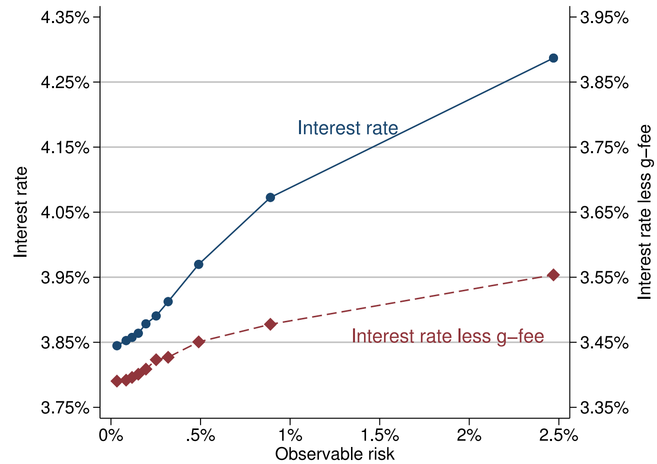

Fig. 1. Interest rates and observable risk.
This figure presents a binned scatterplot of the interest rate and the interest rate net of the total g-fee on observable risk while controlling for origination year-month fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1.
Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac),2016–2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

To compare the pricing for observable risk with other determinants of interest rates, such as markups, Fig. 2 shows the average, 10th percentile, and 90th percentile of interest rates net of g-fees as a function of observable risk.[15] To remove fluctuations in interest rates and enable pooling over the sample period, we focus on the spread relative to the best available rates in a given week, as approximated by the 10th percentile of interest rates net of g-fees for the borrowers in the lowest quartile of observable risk for that week. The 10th percentile of this spread at a given level of observable risk plausibly corresponds to the lowest markups.[16] We find that the 10th percentile increases

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

[16] Consistent with the interpretation that the variation in interest rates for a given level of observable risk largely reflects markups, Figure C.2 in Internet Appendix C.1 shows that the variation is similar even when restricting to a set of mortgages that are relatively straightforward to underwrite: (no cash-out) refinance mortgages where no borrowers are self-employed, there is full income and asset documentation, the LTV ratio is no greater than 70% (which limits the probability of facing constraints due to the appraisal), and the loan amount is greater than the 25th percentile or about $146,000 (which reduces hurdles to low balance lending such as high fixed costs relative to revenue). Additionally, to better control for lender characteristics, Figure C.3 shows that the variation in interest rates is largely similar even after subtracting out

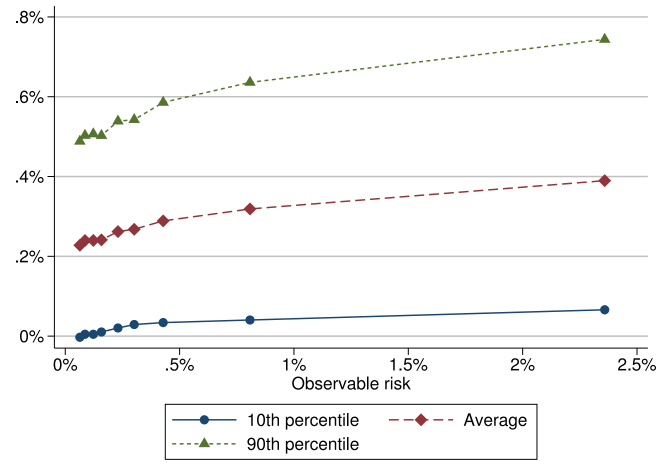

Fig. 2. Interest rates and observable risk: average and dispersion.
This figure shows the 10th percentile, 90th percentile, and average of the spread of the interest rate net of the total g-fee relative to the best available rate for approximate deciles of observable risk. The best available rate is determined by computing the 10th percentile of the interest rate net of the total g-fee for the borrowers in the lowest quartile of observable risk in each week (i.e., observable risk less than 12.5 basis points for the average week). Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1.
Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac),2016–2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

with observable risk at a rate of 1.4 basis points for a 1 percentage point increase in observable risk, which we determine by estimating a quantile regression of the spread of the interest rate net of g-fees relative to the best available rates on observable risk and partialling out by the same fixed effects and controls as in column (5) of Table 1. The fact that the 10th percentile increases with observable risk suggests that markups do not fully account for the association between interest rates and observable risk. However, the shallower slope compared to the average suggests that markups also increase with observable risk.

The positive association between interest rates net of g-fees and observable risk suggests that lenders independently price for default risk. One potential motivation is the threat of repurchases. We find that repurchases occur more frequently for loans with greater observable risk (Figure C.4 in Internet Appendix C.1). While the ex-post rate of repurchases is relatively small (.025% for all loans, or about ten times that rate for defaulting loans), several pieces of evidence suggest that lenders respond meaningfully to the ex-ante threat. A 2015 survey by Fannie Mae indicates that as many as 40% lenders who deliver loans to the GSEs (or Ginnie Mae) and 60% of lenders who originate loans through wholesale channels apply overlays of some kind, citing repurchase risks and costs associated with purchasing and servicing loans that have higher default risks as the primary motivations.[17] Additionally, increased aversion to the ex-ante threat of repurchases is consistent with evidence of lenders increasing their investment in careful underwriting during the period of tightening regulatory oversight following the crisis (Fuster et al., 2024). This inference is based on rising personnel costs, especially for "back end" operations including underwriting, and decreasing loan closings per employee. Furthermore, the publicly available 2021Q1 Mortgage Bankers Performance Report released by the Mortgage Bankers Association indicates that expenses associated with repurchase reserve provisioning are as much as 2% of net production income, again suggesting that lenders are willing to bear costs to handle the threat of repurchases that are relatively large compared to the ex-post rate of repurchases.[18] Finally, besides repurchases, lenders also face the risk of losing the ability to do business with the GSEs (e.g., Keys et al., 2012). Section 4 explains these results with a model of mortgage lender competition in which lenders bear a positive expected loss given default.

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

Discount points. One potential alternative explanation is that riskier borrowers could be more likely to select discount points and lender credits in a way that results in lower upfront costs in return for higher interest rates. However, Figure C.5 in Internet Appendix C.1 shows using the 2018 sample that total origination revenue, which is invariant with respect to the division of revenue between upfront and ongoing charges, is positively associated with observable risk. It also shows that the closing costs and secondary market components of origination revenue both generally increase with observable risk, although the latter is much stronger and appears to drive the overall association between origination revenue and observable risk. Table C.1 shows that the associations between observable risk and either closing costs or secondary marketing income are statistically significant while controlling for the full set of fixed effects and controls. They also generally hold for each of the factors that contribute to observable risk. Finally, even if we do not consider origination revenue, Table C.2 shows that simply controlling for discount points less lender credits as a percentage of the loan amount has little effect on the association between interest rates and observable risk.

Interest rate fluctuations. Another interpretation is that borrowers with greater observable risk may be more likely to apply for a mortgage when interest rates are high. Our baseline specification partially controls for this by including ZIP code by year-quarter fixed effects, but it does not control for short-term fluctuations of interest rates within a quarter. To better investigate this explanation, we merge our sample from MLIS to data on interest rate locks from Optimal Blue, which has the precise lock date. Table 2 shows that the results are similar when controlling for lock rate date fixed effects.[19]

Shopping. Another possibility is that observable risk could be negatively correlated with measures of financial sophistication, such as shopping and financial knowledge, which have been associated with lower interest rates (Bhutta et al., 2021, Malliaris et al., 2021). However, Fig. 2 shows that the 10th percentile of interest rates, which plausibly reflects the most aggressive shoppers for a given level of observable risk, still increases with observable risk. To further investigate this alternative explanation, we examine the association between

the average among loans in the lowest quartile of observable risk for each lender, lender while restricting to nonbanks, or lender-state while restricting to nonbanks.

[17] These findings are based on the 2015Q2 Mortgage Lender Sentiment Survey, which can be accessed here: https://www.fanniemae.com/sites/g/files/koqyhd191/files/migrated-files/resources/file/research/mlss/pdf/mlss-july2015-presentation.pdf.

[18] The Mortgage Bankers Performance Report is based on the Mortgage Bankers Financial Reporting Form, which nonbank lenders submit to the GSEs and Ginnie Mae. It summarizes aggregated information for lenders that volunteer to participate.

[19] Generalizing these results from the GSE segment of the market, Table C.3 in Internet Appendix C.1 shows using the Optimal Blue data that risk characteristics also appear to be priced in loans insured by government agencies, including the Federal Housing Administration (FHA), Department of Veterans Affairs (VA), and Department of Agriculture (USDA). Note that we do not include observable risk as a regressor since we estimate observable risk based on GSE loans, which are generally less risky.

Table 1
Interest rates and observable risk.

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

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

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

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

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

interest rates and observable risk using data from the National Survey of Mortgage Originations (NSMO). The NSMO asks recent mortgage borrowers about their views and experiences related to obtaining their mortgage. The NSMO is conducted on a small subset of loans in the National Mortgage Database (NMDB). The NMDB is a proprietary 5% representative sample of closed-end first-lien mortgages in the U.S. maintained by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau. The NMDB is based on credit bureau data and has precise information about the borrower's interest rate and observable risk characteristics. We use an internal version of the NSMO data at the FHFA that links the NSMO responses to all the characteristics in the NMDB.

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

Table 3 shows the results. As a benchmark, columns (1) and (2) first show that interest rates and interest rates net of g-fees increase with observable risk in the NSMO sample.[20] Columns (3) through (5) then

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

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

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

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

show that this association is robust to including measures of shopping and financial knowledge. Similar to Bhutta et al. (2021), we observe that measures of shopping and financial knowledge are associated with lower interest rates. Finally, motivated by the finding in Agarwal et al. (2020) that borrowers may be willing to accept high interest rates due to fear of rejection, column (6) includes an indicator for a borrower that applies to multiple lenders due to concern over qualifying for a loan. We find that interest rates net of g-fees are positively associated with this indicator, but they are also still positively and significantly related to observable risk. Table C.4 in Internet Appendix C.1 further shows that observable risk is negatively correlated with financial knowledge and positively associated with applying to multiple loans due to concern over qualifying for a loan.

Prepayment risk. The association between interest rates and observable risk could potentially be driven by pricing for prepayment risk.[21] However, we account for prepayments in the following ways. First, one potential determinant of prepayment speed is the loan amount, as borrowers with smaller loans may be less likely to refinance because closing costs are a larger fraction of the principal balance. We account for this channel by controlling for the loan amount. Second, borrowers may use negative discount points to reduce their closing costs while taking on a higher interest rate, which tends to be associated with higher prepayment rates (Zhang, 2022). Figure C.5 and Table C.1 in Internet Appendix C.1 account for this channel by considering the total origination revenue, as discount points only shift the closing cost and secondary marketing income components of origination revenue without affecting the total. Third, we directly control for observable prepayment risk, which is defined analogously to observable risk except based on prepayment within 2 years. We also allow observable prepayment risk to depend on decile indicators for the loan amount. Table C.5 in Internet Appendix C.1 shows that observable prepayment risk has little effect on the association between interest rates and observable risk.

Fallout risk. Lenders could potentially charge higher interest rates to observably risky borrowers to compensate for fallout risk, which refers to the possibility that a borrower who starts an application does not complete it. These incomplete applications impose a cost of lenders' resources that is not directly related to the credit risk of the loan. We measure fallout based on rate locks in Optimal Blue that are not matched to completed transactions MLIS. We restrict to conforming loans in Optimal Blue satisfying analogous sample restrictions as our main MLIS sample. Note that our designation of fallout is imprecise since, in addition to true fallout cases, it also includes loans that are kept in portfolio and failed matches in the merge between Optimal Blue and MLIS. However, most loans in Optimal Blue are unlikely to be held in portfolio since the Optimal Blue platform from which the data is sourced is mostly used by nonbank lenders (Bhutta et al., 2021), which tend to securitize the vast majority of their originations. All things considered, based on our measure of fallout, we find an average fallout rate of about 40%, which does exceed the average fallout rate of about 25% based on the publicly available 2021Q1 Mortgage Bankers Performance Report released by the Mortgage Bankers Association. Having noted these caveats, we find a U-shaped association between our measure of fallout and observable risk (Figure C.6 in Internet Appendix C.1).[22] Therefore, it is unlikely that fallout risk can explain the monotonic relationship between interest rates and observable risk we find in Fig. 1.

[21] 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 et al., 2017).

[22] One potential explanation for the downward-sloping part is that safe borrowers might shop more aggressively. If we run a specification like column (1) of Table C.4 in Internet Appendix C.1 but restrict to borrowers that do not report applying to multiple lenders due to concern about qualifying for a loan, we find that a 1 percentage point increase in observable risk is associated with a 5.3 percentage point lower chance of considering or applying to at least 2 lenders, which is statistically significant at 5%.

Present value multiplier. The GSEs' present value multiplier (PVM) that we use to convert upfront components of the g-fee to an annualized rate could introduce measurement error when computing interest rates net of g-fees. Internet Appendix C.4 provides detailed information about the variation of the PVM in our sample. We show that the PVM has a negative correlation with observable risk, which tends to reduce the association between interest rates net of g-fees and observable risk compared to an only time-varying PVM. We also show that the association between interest rates net of g-fees and observable risk is robust to variation in the PVM, such as imputing the PVM based on the 25th and 75th percentile in the origination year-quarter. Finally, we show that the association is largely similar if we derive an alternative PVM based on the slope of prices in the to-be-announced (TBA) market with respect to coupon rates.

Lender fixed effects. We include fixed effects for the mortgage seller to the GSE, which need not coincide with the originator. We observe that about 31% of loans in our sample are originated via the correspondent channel in which the loan is originated by a correspondent lender and then sold to an aggregator, which then sells it to the GSEs. We implement three approaches for identifying originators, as distinct from sellers, and in each case show that our results are robust to including the associated fixed effects. Columns (1) and (2) of Table C.6 in Internet Appendix C.1 are similar to columns (5) and (6) of Table 1 in the paper except that we restrict to loans originated via retail or broker channels, in which case the lender and seller of the mortgage to the GSEs coincide. In other words, this restriction excludes loans originated via the correspondent channel. Columns (3) and (4) replace the seller identifier with the legal entity identifier (LEI) for the originator, which is available for about 28% of loans in the sample. Columns (5) and (6) instead use Nationwide Mortgage Licensing System and Registry (NMLS) identifiers for the originator. The results are generally similar to Table 1.

Cross-selling. One possible explanation for our findings is cross-selling. For example, banks could offer lower rates to borrowers who are more likely to purchase other services, such as other loans or deposit accounts. Cross-selling is less likely for nonbank lenders since they typically only offer mortgage loans and no other products. We can therefore effectively test the robustness of our results to cross-selling by restricting to nonbanks. Columns (1) and (2) of Table C.7 in Internet Appendix C.1 are similar to columns (5) and (6) of Table 1 in the paper except that we restrict to nonbank sellers. We find that the association between interest rates and observable risk is materially the same as the full sample. The remaining columns employ two approaches for identifying nonbank originators (as distinct from nonbank sellers), which is not a native field in our data. Columns (3) and (4) restrict to nonbank sellers and additionally restrict to the 69% loans in our sample that were originated via retail or broker channels, in which case the lender and seller of the mortgage to the GSEs coincide. After applying this restriction, the coefficient is slightly smaller compared to the baseline specification but remains statistically significant and generally of similar magnitude. Columns (5) and (6) instead restrict to nonbank originators as identified based on the legal entity identifier (LEI). We link the LEI to the reporter panel from the 2018 HMDA, which is the first year that HMDA reports the LEI, and identify nonbanks as lenders identifying as an "independent mortgage banking subsidiary". Although the sample size is smaller due to the limited availability of the LEI in our data, the coefficients are generally similar to the other columns.

3.2. Interest rates and default conditional on observable risk

Whereas the last section focused on the relationship between interest rates and ex-ante observable risk, this section focuses on the relationship between interest rates and unobservable risk, as measured by ex-post defaults while controlling for observable risk. We estimate a regression of the form

$$Default_i = \alpha + \beta(IR - gfee)_i + \gamma Risk_i + \delta \times X_i + \epsilon_i \quad (3)$$

where $Default_i$ indicates a 90-day delinquency within 2 years of origination and the remaining variables are the same as in Eq. (2). We focus on the β coefficient, which represents the extent to which interest rates predict default. We hypothesize that if lenders are both exposed to default risk and conduct independent screening beyond the GSEs' criteria, then the coefficient on β should be positive. In particular, if lenders only judged default risk based on the standard characteristics included in our observable risk measure, then β should be zero after controlling for those characteristics, provided that our controls also capture any mutual correlates of interest rates and defaults conditional on observable risk.

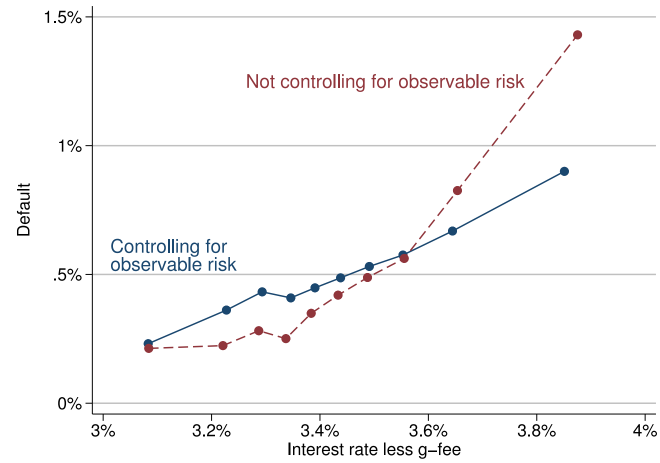

Fig. 3. Interest rates and default.
This figure presents a binned scatterplot of default (multiplied by 100) on the interest rate net of the total g-fee while controlling for origination year-month fixed effects and observable risk, as well as a version that does not control for observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1.
Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac),2016–2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix by more than 25 basis points.

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

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

Table 4
Interest rates and default.

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

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

and Hispanic borrowers; appraisal value decile indicators; an indicator for a refinance loan; an indicator for self-employed borrowers; and an indicator for first-time homebuyers.

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

These results suggest that lenders implement additional screening compared to the determinants of the upfront g-fee. Section 4 incorporates this result into a model of mortgage lender competition by supposing that lenders can invest in improving their underwriting practices, which allows them to observe a partially informative signal of the borrower's default risk conditional on observable risk.

Note that our finding in Table 4 is similar to previous results in the literature showing a positive association between the spread-at-origination (SATO) and default (Gerardi et al., 2023, Fuster and Willen, 2017). However, we additionally present several pieces of evidence in robustness tests below to show that this positive association is not driven by factors such as reverse causation, prepayment risk, or discount points and lender credits. These findings support the idea that the positive association is most likely explained by borrowers' risk-related characteristics beyond observable risk. These additional pieces evidence are especially important for interpreting this positive association as a sign of lenders having better information about borrowers' repayment ability.

To show the robustness of our results, Figure C.7 and Table C.8 in Internet Appendix C.2 show that default is also positively associated with origination revenue in 2018.[23] Also, Table C.9 shows that the association between interest rates and default is robust to controlling for observable prepayment risk, and Table C.10 shows that it is robust to controlling for discount points less lender credits as a percentage of the loan amount. Table C.11 shows that the results are robust to using fixed effects for the originator rather than the seller, and Table C.12 show they are generally robust to restricting to nonbanks.

Robustness to direct effect of interest rates on default. An alternative interpretation for the association between interest rates net of g-fees and observable risk is that higher interest rates might directly (causally) increase default risk. To estimate this direct effect, we examine variation in interest rates that is independent of pricing for default risk. We implement three approaches for doing this that are based on changes in interest rates induced by variation in the upfront g-fee or prices in the to-be-announced (TBA) market. 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, TBA prices, or lender markups.

Our first approach to examine the direct effect of interest rates on default leverages discontinuities in the upfront g-fee as a function of the credit score. In particular, we focus on discontinuities where the upfront g-fee changes by at least 50 basis points (as a percentage of the loan amount). We implement a regression discontinuity approach by restricting to loans near these shifts and examining how interest rates and defaults change exactly at the shifts.

In more detail, as mentioned in Section 2.1, a component of the upfront g-fee varies based on a grid defined by ranges for the credit score and LTV ratio. For loans in our sample period with an LTV between

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

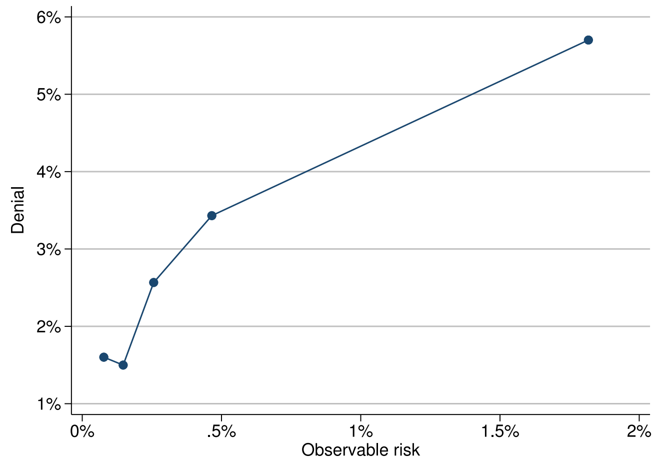

Fig. 4. Application denials and observable risk.
This figure presents a binned scatterplot of the denial rate for mortgages accepted by the GSEs' automated underwriting systems on observable risk. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. Observable risk is estimated using the MLIS data.
Source: confidential HMDA, 2018, restricting to approved or denied applications accepted by the GSE automated underwriting systems for conventional, 30-year, purchase or no cash-out refinance, first lien loan applications for one-unit, owner-occupied, single-family non-manufactured houses and excluding high balance loans exceeding the base conforming loan limit and loans with a combined loan-to-value ratio exceeding 80%. We also exclude denials due to incomplete applications and insufficient cash at closing.

60% and 80%, the upfront g-fee matrix exhibits a discrete decline of at least 50 basis points as the credit score surpasses the credit score thresholds in the following seven cases: 660 for LTV ratios between 70.01% and 75%, 680 for LTV ratios between 60.01% and 70%, 680 for LTV ratios between 70.01% and 75%, 680 for LTV ratios between 75.01% and 80%, 700 conditional on LTV between 75.01% and 80%, 720 conditional on LTV between 70.01% and 75%, 720 conditional on LTV between 75.01% and 80%. To focus on only changes in interest rates at these thresholds and minimize the possibility that they could also affect acceptance decisions, we restrict to loans with a DTI of up to 43%. This restriction is based on the observation that 45% is the lowest DTI ratio that appears to affect acceptance decisions for GSE loans (Bosshardt et al., 2024). We also restrict to loans where the total upfront g-fee is exactly equal to the component determined by LTV and credit score. On this subsample, we regress the interest rate on an indicator for having a credit score greater than or equal to the respective threshold times the change in the upfront g-fee at the threshold. We control for threshold group (i.e., an indicator for loans within a 5-point range of a given threshold) by year-month fixed effects and credit score (minus the respective threshold) times the threshold group indicators.

Fig. 5(a) combines loans from all seven cases and shows that interest rates exhibit a discrete reduction as the credit score surpasses the respective threshold. Column (1) of Table 5 shows that a 100 basis point increase in the upfront g-fee at the thresholds is associated with a 17.5 basis point and statistically significant increase in the interest rate. By contrast, Fig. 5(b) indicates no discontinuous changes in default rates at the threshold. Column (2) indicates a statistically insignificant association between the upfront g-fee and defaults. Column (3) similarly indicates an insignificant relationship between defaults and interest rates when instrumenting the latter by the change in the upfront g-fee at the thresholds. Table C.13 in Internet Appendix C.2 additionally shows how interest rates and defaults vary at the thresholds for each of the seven cases separately. Interest rates decrease in a narrow range of about 7 to 9 basis points for thresholds with a 0.5 basis point decline in the upfront g-fee, or by 17 to 18 basis points for thresholds

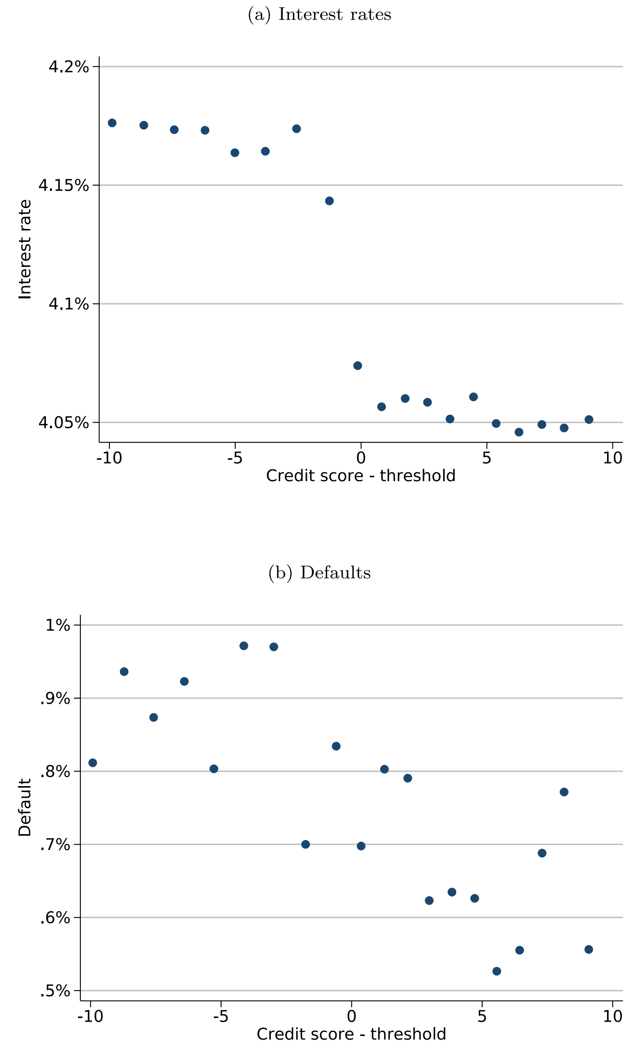

Fig. 5. Interest rates and defaults at the g-fee thresholds.
These figures restrict to loans with a loan-to-value (LTV) ratio and credit score such that the credit score is within 10 points of a threshold where the upfront g-fee changes by at least 50 basis points. Fig. 5(a) shows a binned scatterplot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

with a 1 basis point decline in the upfront g-fee. There is greater variability in the estimated associations between the thresholds and defaults, which could be partially due to the low rate of defaults in the sample. However, all the estimates are statistically insignificant and roughly evenly split around zero.

In the second approach, we instrument the interest rate with prices in the to-be-announced (TBA) market. The TBA market is a forward market for MBS in which the exact pools are not specified by the seller until shortly before settlement. The TBA market is often used by lenders to fix the sale price of a loan at the time of a rate lock but before the loan is originated. The TBA price varies with the MBS coupon rate. A positive shift in TBA prices allows lenders to charge lower interest rates to achieve the same revenue. Column (1) of Table 5 shows that an increase in the TBA price for a given coupon generally passes through

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

	(1) IR (First stage)	(2) Default (Red. form)	(3) Default (IV)	(4) IR (First stage)	(5) Default (Red. form)	(6) Default (IV)
IR			−0.864			−0.125
			(−0.52)			(−0.54)
Above threshold × upfront g-fee	0.175***	−0.151				
	(22.91)	(−0.52)				
TBA price				−0.110***	0.014	
				(−137.93)	(0.54)	
Observations	38,292	38,292	38,292	130,787	130,787	130,787
R^2	0.532	0.007	−0.002	0.718	0.289	−0.000
Threshold ×Year-month FE	Yes	Yes	Yes	No	No	No
Threshold dummy ×Credit score	Yes	Yes	Yes	No	No	No
ZIP ×Year-quarter FE	No	No	No	Yes	Yes	Yes
Seller ×Year-quarter FE	No	No	No	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes

Note: Columns (1) through (3) restrict to loans with a loan-to-value (LTV) ratio and credit score such that the credit score is within 5 points of a threshold where the upfront g-fee changes by at least 50 basis points. Column (1) regresses the interest rate on an indicator for having a credit score greater than or equal to the respective threshold times the change in the upfront g-fee at the threshold, and it controls for threshold group (i.e., an indicator for loans within a 5-point range of a given threshold) by year-month fixed effects and credit score (minus the respective threshold) times the threshold group indicators. Column (2) is similar to column (1) except that the dependent variable is an indicator for default (multiplied by 100). Column (3) is similar to column (2) except that we regress the default indicator on interest rates, which we instrument by the change in the upfront g-fee at the respective threshold. Column (4) regresses the interest rate on the to-be-announced (TBA) market price for a 3.5% coupon as of the lock date while controlling for ZIP code by year-quarter fixed effects and seller by year-quarter fixed effects. Observable risk is the estimated probability of default based on the credit score, loan-to-value ratio, and debt-to-income ratio as described in Section 2.1. We also include the following controls: loan amount decile indicators and an indicator for full income and asset documentation. Column (5) regresses an indicator for default (multiplied by 100) on the TBA price. Column (6) regresses the default indicator on the interest rate, which we instrument by the TBA price. T-statistics computed using robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Source: Mortgage Loan Information System (Fannie Mae and Freddie Mac), 2016–2017, restricting to fixed rate, 30-year, purchase or no cash-out refinance loans for one-unit, owner-occupied, single-family detached houses and excluding high balance loans exceeding the base conforming loan limit, loans with subordinate financing, loans with a loan-to-value ratio exceeding 80%, and loans where the upfront g-fee deviates from the first table of the g-fee matrix. Columns (1) through (3) additionally restrict to loans with a DTI up to 43%. Columns (4) through (6) restrict MLIS merged with Optimal Blue. TBA price data comes from Bloomberg.

to lower interest rates.[24] We can then instrument the effect of higher interest rates on defaults based on changes in TBA prices. Column (2) shows in a reduced form regression that defaults are not significantly associated with changes in TBA prices, and column (3) shows that they are also not significantly associated with the instrumented variation in interest rates.

Our two approaches for estimating the effect of interest rates on defaults, namely the regression discontinuity in columns 1-3 of Table 5 and the TBA price instrument in columns 4–6 of Table 5, are complementary due to their different strengths and weaknesses. The regression discontinuity uses micro-level variation, but it restricts to a relatively small sample near the thresholds and has lower power. The TBA price instrument explains a large share of the variation in interest rates but it depends on macro-level variation, which could confound the results if, for example, TBA prices are associated with certain macroeconomic conditions.

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

Column (1) of Table C.14 shows in a first-stage regression that a 100 basis point increase in up-front g-fee is associated with 16.3 basis point increase in monthly mortgage payments. As shown in Figure C.8 in Internet Appendix C.2, residual variation in the interest rate spans about 25 basis points in the interest rate. Column (2) of Table C.14 then indicates a small and statistically insignificant relationship between the residual variation in the upfront g-fee and defaults. Column (3) similarly indicates a negligible relationship between interest rates, instrumented by the upfront g-fee, and defaults.

Note that our setting contrasts in several ways from existing studies that find a larger effect of interest rates on default (Fuster and Willen, 2017, Di Maggio et al., 2017, and Gupta, 2019). For one, we focus on interest rates determined at origination, whereas the studies from the literature focus on variation due to interest rate resets for adjustable-rate mortgages. Interest rate resets plausibly have a stronger effect since household income could have changed significantly from the time of mortgage origination, resulting in some households having significantly higher monthly mortgage payments relative to income. Additionally, households could be inattentive and unprepared for the effect of a reset (Gupta, 2019). Moreover, we focus on a relatively safe sample of post-crisis GSE loans, whereas the primary sample in each of these papers focuses on much riskier non-agency loans originated in the volatile 2000s decade. The level of baseline risk is another factor that plausibly affects the impact of interest rates. For example, Fuster and Willen (2017) and Di Maggio et al. (2017) show that the effect of ex-post interest rate changes on defaults increases with risk characteristics such as high LTV ratios and low credit scores.

3.3. Denials and observable risk

For this observation, we use the confidential HMDA data in 2018 to examine the extent to which lenders deny applications that are

[24] We use the Bloomberg series "FNCL X G0 Mtge" for coupons X.

accepted by the GSEs' automated underwriting systems (AUSs). Analogous to the MLIS sample, we restrict to applications for conventional, 30-year, purchase or no cash-out refinance, first lien loans for one-unit, owner-occupied, single-family non-manufactured houses. We also exclude applications for high balance loans exceeding the national baseline conforming loan limit and applications with an LTV ratio exceeding 80%. We further restrict to mortgages that are processed by exactly one AUS, which is either Desktop Underwriter (for Fannie Mae) or Loan Prospector (for Freddie Mac), and for which the result of the AUS is "Approve/Eligible" or "Accept."[25] 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.[26] Note that we compute observable risk as a function of credit score, LTV, and DTI based on the model estimated with the MLIS data.[27]

Fig. 4 shows that denials increase with observable risk, ranging from about 1.60% for borrowers with 0.08% observable risk to 5.69% for borrowers with 1.82% observable risk. As a robustness check, Figure C.9 in Internet Appendix C.3 shows that a clear positive association remains if we remove denials due to any of the other reasons. Note that these results are similar to Bhutta et al. (2025), who also show that lender accept/reject decisions do not fully coincide with the GSEs' AUSs. However, they focus on racial and ethnic disparities of lender and AUS denials and show how they vary across credit scores, whereas our focus is on the relationship between lender denials of AUS-accepted applications and observable risk.

3.4. Interpretation

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

4. Model

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

4.1. Overview

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

4.2. Consumer problem

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

$$u_{ij} = \mu_i - \alpha_i r_j + \epsilon_{ij}, \tag{4}$$

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

Consumers choose between the lenders and the outside option to maximize their utility. Utility maximization determines the probability of obtaining a loan from each lender as follows:[28]

$$s_j = \frac{\exp(\mu_i - \alpha_i r_j)}{1 + \sum_{j=1}^{n} \exp(\mu_i - \alpha_i r_j)}. \tag{5}$$

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

4.3. Lender problem

Screening. There are two unobserved quality types of consumers: a mass 1 of type r consumers that repay and a mass q of type d consumers that default. Lenders screen consumers by drawing a signal z_i that indicates "low" (L), "medium" (M), or "high" (H) risk. For simplicity, we assume that a given consumer produces the same signal for all lenders.[29] The informativeness of the signal is determined by a lender's information level ψ_j. In particular, conditional on ψ_j, the distributions of the signals generated by the two types of consumers are given by

$$P(z_i|d;\psi_j) = \left\{ \begin{array}{ll} L, & \text{with probability } \epsilon(1-\psi_j) \\ M, & \text{with probability } 1-\psi_j-\epsilon(1-\phi)(1-\psi) \\ H, & \text{with probability } \psi_j - \epsilon\phi(1-\psi_j) \end{array} \right\}, \tag{6}$$

$$P(z_i|r;\psi_j) = \left\{ \begin{array}{ll} L, & \text{with probability } \psi_j - \epsilon\phi(1-\psi_j) \\ M, & \text{with probability } 1-\psi_j-\epsilon(1-\phi)(1-\psi_j) \\ H, & \text{with probability } \epsilon(1-\psi_j) \end{array} \right\}. \tag{7}$$

The exogenous parameter ϵ represents the tendency for repaying consumers to generate H signals and defaulting borrowers to generate L signals. The parameter ϕ represents the extent to which the mass for these signals comes from the M signal or the remaining signal (L for repaying consumers and H for defaulting consumers). Note that the default rate associated with each type of signal is $\delta^L = \frac{q\epsilon(1-\psi_j)}{q\epsilon(1-\psi_j)+\psi_j-\epsilon\phi(1-\psi_j)}$, $\delta^M = \frac{q}{1+q}$, and $\delta^H = \frac{q(\psi_j-\epsilon\phi(1-\psi_j))}{q(\psi_j-\epsilon\phi(1-\psi_j))+\epsilon(1-\psi_j)}$.

Each lender chooses ψ_j at a cost of

$$c(\psi_j) = \frac{k}{(1-\psi_j)^2} - k, \tag{8}$$

[25] 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.

[26] In particular, we exclude applications for which any of potentially multiple reasons for denial refers to an incomplete application or insufficient cash at closing. Note that 89% of denied applications in our sample only have one denial reason. See Table C.15 in Internet Appendix C.3 for the fraction of denials attributable to each reason.

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

[28] See Train (2009) for a proof.

[29] Our results are robust to an alternative model in which lenders draw different signals (see Internet Appendix F).

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

Profit maximization. For simplicity, we assume that a consumer's interest rate sensitivity is observable to lenders. Therefore, we can focus on the lender's problem for a set of consumers with a given interest rate sensitivity α. Suppose that a lender's cost of funding is equal to ρ. If the loan defaults, then the lender incurs an expected loss given default of $\omega \geq 0$ due to, for example, repurchase risk (Fuster et al., 2024). If a lender were to lend to consumers associated with each type of signal, then the lender's expected profits can be expressed as

$$\begin{aligned}\Pi_j &= (\psi_j - \epsilon\phi(1-\psi_j) + q\epsilon(1-\psi_j))s_j^L\left(r_j^L(1-\delta^L) - (\rho+\omega\delta^L)\right)\\ &\quad + (1-\psi_j)(1+q)(1-\epsilon(1-\phi))s_j^M\left(r_j^M(1-\delta^M) - (\rho+\omega\delta^M)\right)\\ &\quad + (q(\psi_j - \epsilon\phi(1-\psi_j)) + \epsilon(1-\psi_j))s_j^H\left(r_j^H(1-\delta^H) - (\rho+\omega\delta^H)\right)\\ &\quad - c(\psi_j), \end{aligned} \tag{9}$$

where for each signal z the term $r_j^z(1-\delta^z)$ is the expected revenues from lending to consumers with that signal and $-(\rho+\omega\delta^L)$ is the expected costs. The resulting profit is multiplied by the fraction of consumers that apply for a loan s^z and the mass of such signals in the borrower pool.

A lender has an incentive to lend to borrowers with a given signal z as long as it can charge an interest rate at least equal to the level which generates zero profits, which is $\frac{\rho+\omega\delta^z}{1-\delta^z}$. However, there exists a bound B on the interest rate a lender can charge. For example, B could represent regulations that make it difficult for lenders to charge high interest rates, such as the Home Ownership and Equity Protection Act (HOEPA), which burdens lenders with additional disclosures, prohibitions, and counseling requirements when originating a loan with high interest rates or fees. Motivated by the evidence in Fig. 4 that lenders reject some borrowers, we assume $B < \frac{\rho+\omega\delta^H}{1-\delta^H}$, which implies no lending to H-signal consumers. However, we assume B is high enough that it does not constrain lending to M-signal borrowers.

Each lender chooses the interest rate for each signal type r_j^z and information level ψ_j to maximize expected profits.[30] The first order conditions for r_j^z and ψ_j yield, respectively,[31]

$$r_j^z = \frac{\rho+\omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s_j^z)}, \tag{10}$$

$$\begin{aligned}c'(\psi_j) &= (1+\epsilon\phi - q\epsilon)s_j^L\left(r_j^L - \rho\right) - (1+q)(1-\epsilon(1-\phi))s_j^M\\ &\quad \times \left(r_j^M(1-\delta^M) - (\rho+\omega\delta^M)\right).\end{aligned} \tag{11}$$

In Eq. (10), the term $\frac{\rho+\omega\delta_j^z}{1-\delta_j^z}$ represents a lender's zero-profits interest rate, which we call the origination cost. The remaining term $\frac{1}{\alpha(1-s_j^z)}$ represents the markup. In Eq. (11), the left-hand side represents the marginal cost of increasing the information level, whereas the right-hand side corresponds to the marginal benefit derived from having a greater share of the portfolio consisting of L-signal consumers. Lending to L-signal consumers is preferable since lenders charge them lower interest rates, which causes fewer of them to substitute to the outside option.[32]

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

[31] See Appendix A for a proof.

[32] To see this, we can substitute Eq. (10) into Eq. (11), whereby the latter becomes $c'(\psi_j) = \frac{s_j^L}{\alpha(1-s_j^L)} - \frac{s_j^M}{\alpha(1-s_j^M)}$. The right-hand side therefore has the same sign as $s_j^L - s_j^M$, which is nonnegative since L-signal consumers have lower interest rates for a given market share by Eq. (10) and the market shares are decreasing in the interest rate by Eq. (5).

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

1. The *denial rate* is equal to the fraction of H-signal consumers: $\frac{\epsilon(1-\psi)+q(\psi-\epsilon\phi(1-\psi))}{1+q}$.
2. The *default rate* is equal to the fraction of defaulting consumers among consumers that receive a loan. This can be expressed as a weighted average $d = \sum_z P^z d^z$, where the weights correspond to the fraction of consumers with a given signal among those that are offered a loan, i.e.,

$$P^L = \frac{\psi - \epsilon\phi(1-\psi) + q\epsilon(1-\psi)}{\psi - \epsilon\phi(1-\psi) + q\epsilon(1-\psi) + (1+q)((1-\psi) - \epsilon(1-\phi)(1-\psi))} \tag{12}$$

$$P^M = \frac{(1+q)((1-\psi) - \epsilon(1-\phi)(1-\psi))}{\psi - \epsilon\phi(1-\psi) + q\epsilon(1-\psi) + (1+q)((1-\psi) - \epsilon(1-\phi)(1-\psi))} \tag{13}$$

3. The *signal-weighted average interest rate* is $r = \sum_z P^z r^z$. Note that references to the interest rate in the model refer specifically to the signal-weighted average interest rate unless otherwise specified.

4.4. Model estimation

We find the parameters to quantitatively match the observations in Section 3 using GMM, the generalized method of moments (Hansen, 1982, Hansen, 2022). We focus on how the model outcomes vary with the fraction of defaulting consumers λ_d, which is also equal to $\frac{q}{1+q}$. We therefore normalize the cost of funding ρ to be zero, as it only serves to create a level shift of interest rates that can be used to capture time-varying factors that are not the focus of this exercise. We select $\phi = \frac{1}{2}$ and show in Appendix D.4 that ϕ does not have a material effect on the results. We assume that the interest rate sensitivity for a given level of observable risk is uniformly distributed with probability density function $U[\alpha(\lambda_d) - \sigma, \alpha(\lambda_d) + \sigma]$, where the mean $\alpha(\lambda_d)$ linearly varies with λ_d according to $\alpha(\lambda_d) = \alpha_0 + \alpha_1\lambda_d$. We estimate the mean value of owning a home, which we denote as μ.

The number of lenders n is directly selected to be 2, which is the median number of lenders that are seriously considered by borrowers according to the National Survey of Mortgage Originations (Bhutta et al., 2021, Alexandrov and Koulayev, 2018).[33]

The remaining 7 parameters (μ, α_0, α_1, σ, ω, k, and ϵ) are selected to match 8 moments based on the observations reported in Section 3.

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

1. The variation of interest rates net of g-fees with respect to observable risk. Based on column (5) of Fig. 1, we find that an increase in observable risk by 1 percentage point is on average associated with a .042 percentage point increase in interest rates net of g-fees. We determine the model analog by computing the slope of the signal-weighted interest rate with respect to observable risk locally and then taking a weighted average over observable risk based on the empirical distribution.
2. The level of the interest rate net of g-fees for consumers with the lowest level of observable risk after subtracting the time-varying portion of interest rates. Based on Fig. 2, this is equal to .23 percentage points.
3. The variation of the 10th percentile of interest rates net of g-fees with respect to observable risk. We determine this empirically by estimating a quantile regression of the spread of the interest rate net of g-fees relative to the best available rates on observable risk and partialling out by the same fixed effects and controls

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

Table 6
Estimated parameters.

Parameter	Value	Standard error
Borrower utility of borrowing (μ)	5.177	(2.680)
Level of sensitivity to interest rate (α_0)	8.342	(.422)
Variation in sensitivity to interest rate (α_1)	−46.682	(.153)
Sensitivity to interest rate dispersion (σ)	6.627	(.331)
Lender loss given default (ω)	2.709	(.329)
Information cost scale (k)	8.941e−05	(2.638e−04)
Signal distribution (ϵ)	.0349	(.198)

Note: Parameters related to the interest rate sensitivity (α_0, α_1, and σ) are scaled such that the interest rate sensitivity corresponds to the decrease in utility associated with a 1 percentage point increase in the interest rate. The lender loss given default ω is scaled as a percentage of the loaned amount. The information cost scale k is scaled in a manner consistent with lender profits in Eq. (9) being expressed as a percentage of the loaned amount.

Table 7
Empirical and model generated moments.

Variable	Empirical	Model (base)
Slope of interest rate wrt. obs. risk	0.0419	0.0686
Interest rate for borrowers with low obs. risk	0.0023	0.0024
Slope of 10th pctile. interest rate wrt. obs. risk	0.0140	0.0318
Difference between 90th pctile. and 10th pctile. for low obs. risk	0.0049	0.0052
Slope of default wrt. interest rate (safe)	0.1120	0.0899
Slope of default wrt. interest rate (risky)	0.6499	0.6686
Slope of denial rate to obs. risk	1.9199	1.6432
Denial rate for borrowers with low obs. risk	0.0160	0.0134

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

as in column (5) of Table 1, which is similar to the slope of the 10th percentile interest rate in Fig. 2. We find that an increase in observable risk by 1 percentage point is on average associated with a .014 percentage point increase in the 10th percentile.

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

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

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

Moment related to the correlation between denials and observable risk:

7. The variation in the denial rate with respect to observable risk. We determine this empirically by regressing an indicator for denial on observable risk. We find that an increase in observable risk by 1 percentage point is on average associated with a 1.92 percentage point increase in denials.
8. The level of the denial rate for consumers with the lowest level of observable risk. Based on Fig. 4, this is equal to 1.6 percent.

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

Table 8 shows the sensitivity of each of the moments to each of the parameters relative to the estimated parameters. For each moment there is at least one parameter such that a 10% change in the parameter induces at least a 9% change in the moment. This observation indicates that the moments respond to the parameters and supports the identification of the model. While the moments simultaneously determine all the parameters, some intuitive links are as follows. The variation of interest rates net of g-fees with respect to observable risk (moment 1) is significantly influenced by the loss given default ω, which contributes to origination costs, and the variation in the sensitivity to the interest rate α_1, which contributes to markups.[34] The level of the interest rate for consumers with the lowest level of observable risk (moment 2) relates most to the average sensitivity to the interest rate for these consumers, α_0. The variation of the 10th percentile of interest rates net of g-fees (moment 3) is strongly influenced ω. The difference between the 90th percentile and 10th percentile of interest rates (moment 4) is strongly influenced by the dispersion in the sensitivity of interest rates conditional on observable risk, σ.[35] The slope of the denial rate (moment 7) relates most to the information cost k. It is also one of the moments most strongly affected by the consumer's value of the transaction relative to the outside option μ, which is related to the fact that the benefit of acquiring information derives from the lower tendency for L-signal consumers to substitute to the outside option. The level of the denial rate for low risk borrowers (moment 8) is the moment that is most strongly affected by ϵ.

4.5. Alternative estimation based on incomplete pass-through

One potential drawback of our estimation approach is that the parameters for the interest rate sensitivity α, which determines lender

[34] It is also strongly influenced by the interest rate sensitivity for low-risk borrowers α_0, since the rate of change in the markup term in Eq. (10) decreases with α.

[35] It is also strongly influenced by α_0 since the rate of change in the markup term in Eq. (10) decreases with α.

Table 8
Sensitivity analysis.

(a) Levels

	Base	μ	α_0	α_1	σ	ω	k	ϵ
IR slope: avg	.0686	.0677	.0602	.08	.0686	.0737	.0697	.0689
IR level: avg	.0024	.0024	.0022	.0024	.0024	.0024	.0024	.0024
IR slope: p10	.0318	.0324	.0311	.0326	.0316	.036	.0321	.0318
IR level: p90-p10	.0052	.0052	.0038	.0052	.0058	.0052	.0052	.0052
Corr. IR and default (safe)	.0899	.0893	−.2896	.0897	.0835	.0904	−.0681	.0903
Corr. IR and default (risky)	.6686	.6528	.9855	.6879	.5884	.687	.6559	.671
Denial slope	1.6432	1.6072	1.569	1.8708	1.6432	1.6683	1.4992	1.6654
Denial level (low risk)	.0134	.0134	.0138	.0134	.0134	.0134	.0151	.0138

(b) Relative changes

	μ	α_0	α_1	σ	ω	k	ϵ
IR slope: avg	−.0135	−.1227	.1658	0	.0747	.0163	.0045
IR level: avg	.0076	−.0909	.0009	0	.0012	.0011	−.0001
IR slope: p10	.0179	−.0205	.0262	−.0059	.1314	.0092	.0001
IR level: p90-p10	.0076	−.2739	.0032	.1096	−.0001	−.0039	−.0001
Corr. IR and default (safe)	−.0068	−4.2208	−.0023	−.0717	.0054	−1.757	.0048
Corr. IR and default (risky)	−.0235	.474	.0289	−.1198	.0275	−.019	.0037
Denial: slope	−.0219	−.0452	.1385	0	.0152	−.0876	.0135
Denial level (low risk)	.0005	.0264	−.0002	0	−.0021	.1218	.0266

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

markups, are mostly determined by the variation in interest rates net of g-fees, as largely summarized in Fig. 2. Price variation need not correspond to markups, as it can also be due to, for example, variation in marginal costs and service quality across lenders. While Figure C.3 in Internet Appendix C.1 shows that the variation in interest rates net of g-fees is mostly similar even after effectively subtracting lender fixed effects, we also implement a completely different approach to estimate α based on the incomplete pass-through of changes in the secondary market.

Our approach is based on the observation that the price relative to par that a lender achieves in the secondary market depends on how the interest rate compares to the current coupon yield on MBS. An increase in the yield causes lenders to increase the interest rate to achieve the same revenue, which causes consumers to obtain fewer loans. However, if lenders charge markups, then they can adjust to an increase in the yield partly by decreasing the markup, resulting interest rates increasing by less than the implied cost. Internet Appendix D.3 expands on this idea and derives an independent estimate of α based on the response of interest rates and loan quantities to weekly changes in the yield. As a brief summary, we modify the model to incorporate the effect of the current coupon yield on a lender's revenue, which changes Eq. (10) to

$$r_j^z - CCY = \frac{\rho_j + \omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s_j^z)}, \tag{14}$$

Based on this relationship and the determination of market shares like in Eq. (5), changes in the yield lead to changes in interest rates and origination volumes (which in the model corresponds to $\sum_{j=1}^{n} s_j$). In particular, if CCY in (14) increases, then the interest rate r_j^z increases to maintain the equality. However, this increase in the interest rate causes the market share s_j^z to decrease, which causes the right hand side of (14) to decrease. As a result, the interest rate increases by less than the change in CCY. The magnitude of the interest rate sensitivity α determines the relative magnitude of these changes. Intuitively, a small pass-through gap – that is, the difference between the change in the secondary market yield and the change in interest rates charged by lenders – relative to the change in quantities is consistent with a higher interest rate sensitivity α.

We find that an increase in the yield by 10 basis points is associated with a 13.5% decline in originations and a 6.3 (7.7) basis point increase in the weekly mean (median) of interest rates. We find the resulting estimate for the average α is around 5.2 to 9.6, which is similar to our baseline estimate for the average α of around 8.2 (obtained by $\alpha_0 - .005\alpha_1$ using the parameters in Table 6 and the average observable risk of .005).

5. Counterfactual: GSE loans effectively without intermediaries

In this section, we first show that a counterfactual effectively without intermediaries can in principle lead to higher or lower interest rates due to the competing effects of higher origination costs (due to less screening) and lower markups. We then use the estimated model to determine that the counterfactual would reduce interest rates for all consumers, but to a lesser extent for observably risky consumers. We also discuss a potential implementation of the counterfactual through a standardized mortgage application platform.

5.1. Counterfactual definition

We consider a counterfactual in which all applications that are accepted by the GSEs' underwriting criteria are offered a loan and the interest rate conditional on a given level of observable risk is determined by a zero-profits condition. In particular, the counterfactual is effectively without intermediaries since accept/reject decisions and interest rates are determined without any influence from third parties. We also assume that lenders are no longer distinguished and therefore eliminate the idiosyncratic shocks ϵ_{ij}.[36] We can summarize some key properties of the counterfactual as follows:

1. Denial rate = 0.
2. Default rate = $\frac{q}{1+q}$, which is also equal to λ_d.
3. Interest rate = $\frac{\rho+\omega\lambda_d}{1-\lambda_d}$, which we denote as $r_{counterfactual}$.

To determine which system (i.e., the baseline model with intermediaries or the counterfactual) yields greater benefits for consumers, we primarily consider which generates a lower average interest rate. On the one hand, the baseline model can lead to lower origination costs since lenders screen out some of the consumers that would default.

[36] Note that the counterfactual yields the same result as a market with perfect competition.

On the other hand, the baseline model also exhibits markups since lenders take advantage of distinguishing characteristics that are valued by consumers. To summarize this tradeoff, we can write the difference as

$$r_{baseline} - r_{counterfactual} = \sum_z P^z \underbrace{\left[\frac{\rho + \omega\delta^z}{1-\delta^z} + \frac{1}{\alpha(1-s^z)}\right]}_{r^z} - \frac{\rho + \omega\lambda_d}{1-\lambda_d}$$

$$= \sum_z P^z \left[\underbrace{\frac{\rho + \omega\delta^z}{1-\delta^z} - \frac{\rho + \omega\lambda_d}{1-\lambda_d}}_{\leq 0} + \underbrace{\frac{1}{\alpha(1-s^z)}}_{>0}\right]. \tag{15}$$

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

Note that we abstract from various other potential benefits and costs that are outside the scope of the model. For example, independent risk pricing by lenders can provide a signal to regulators and policymakers about emerging risks in mortgage markets.[37]

5.2. Model results

Fig. 6 compares the baseline model and the counterfactual for varying levels of λ_d, which is monotonically related to observable risk. We find that interest rates are higher for the baseline model for all levels of λ_d. Although intermediaries reduce origination costs by as much as 60%, they are still associated with a higher interest rate due to substantial markups. The difference between the interest rates decreases with λ_d, which reflects the greater cost-saving potential of intermediaries for riskier market segments.[38] Besides the interest rate, Internet Appendix D.1 also compares the baseline model and the counterfactual with respect to the total surplus and its components.

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

Finally, Figure D.3 in Internet Appendix D.2 illustrates the role of competition. As the number of lenders increases, markups naturally decrease. This in turn reduces the incentive to invest in screening, resulting in a higher default rate and origination cost. Overall, stronger competition tends to reduce the differences between the baseline model and the counterfactual.[39]

5.3. Discussion on the implementation of the counterfactual

The substantial markups in the baseline model are partly driven by limited shopping, as reflected by the fact that the number of lenders seriously considered by consumers n is only equal to 2, consistent with the empirical median. This limited shopping is unlikely to be due to a lack of options, as there are about 1700 lenders in the sample and an average of 35 lenders per county. Instead, it more likely reflects search frictions, such as having to submit detailed information to lenders to obtain and compare price quotes.

We therefore consider how these markups could potentially be reduced by more closely emulating the counterfactual. Theoretically, the counterfactual produces the same result as a market in which lenders face perfect competition and have no market power. In terms of practical implementation, it can also be likened to a market in which borrowers apply for GSE loans through a standardized common mortgage application platform across lenders. Such a platform would verify the borrower's information and confirm eligibility of the application for GSE mortgages through the GSEs' automated underwriting system (AUS), then disseminate the information of AUS approved borrowers to lenders. Lenders could then make binding offers based on the information provided on the platform. Such a platform could ensure that lenders have access to the same information as well as allow borrowers to easily apply to and compare offers from many lenders. Note that an important requirement for this platform to work is to remove the putback risk. A potential concern is that intermediaries without skin in the game would have weaker incentives to avoid sending misleading information to the automated underwriting systems, resulting in more fraud. However, the verification process would be implemented by the platform before the application is sent to competitive lenders. Moreover, for a significant share of borrowers – those with low leverage and full income documentation – this verification process can be fully automated at a relatively low cost.

6. Extension: heterogeneous lenders

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

6.1. Empirical variation in intermediation patterns by lender type

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

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

[37] Note that pricing of credit risk for GSE loans also occurs via their credit risk transfer (CRT) securities, which allow investors to purchase cash flows from the GSEs that can vary with the performance of the reference mortgages. Since CRT securities refer to a pool of mortgages, they offer a relatively aggregated signal, whereas pricing by lenders occurs at the loan level. Furthermore, mispricing of risk by the g-fee could potentially also be inferred based on the rate at which banks keep loans on their portfolio, but that is also outside the scope of our analysis.

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

[39] Note, however, that the baseline model does not converge to the counterfactual as n increases, as lenders can always charge positive markups due to their product differentiation that appeals to consumers' idiosyncratic tastes.

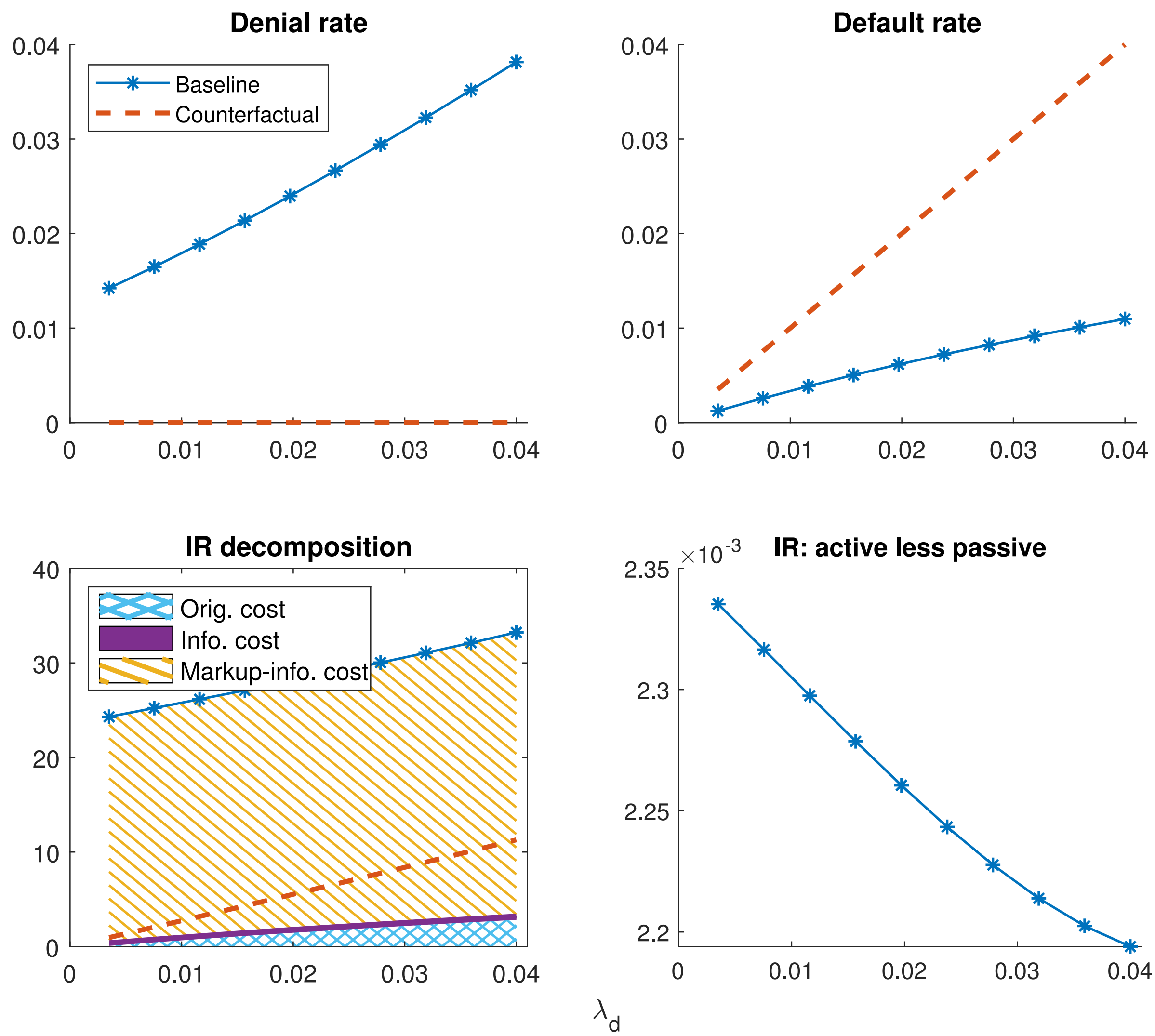

Fig. 6. The Effects of Intermediaries.
These figures show various features of the model of the baseline model (in which lenders screen the applicant, approve or deny the application, and engage in imperfect competition to determine the interest rate) and the counterfactual (a setting where all applications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

that jointly incorporates credit scores, higher debt-to-income ratios, and loan-to-value ratios.[40]

Second, Fig. 7(b) shows that nonbanks are associated with higher interest rates net of g-fees conditional on observable risk. Column (2) of Table 9 shows that the average difference is about 4.8 basis points, while column (3) shows that the difference slightly increases with observable risk.[41] This observation, which is similar to other results in the literature (e.g., Buchak et al., 2018, Benson et al., 2023), is consistent with nonbanks having higher funding costs, possibly due to nonbanks' use of warehouse financing lines rather than insured deposits (e.g., Jiang, 2023). It is also consistent with nonbanks exhibiting higher default rates conditional on observable risk, as described further in the next paragraph.

Third, Fig. 7(c) shows that nonbanks are associated with higher default rates conditional on observable risk. Column (4) of Table 9 shows that the average difference between banks and nonbanks is 16.8 basis points, which is substantial relative to the average default rate of 50 basis points. Column (5) shows that the difference is only 2.6 basis points and statistically insignificant for low-risk borrowers, but it increases by 27.8 basis points for each percentage point of observable risk.[42] This observation updates previous work indicating that the association between nonbanks and default for GSE loans is small in

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

[41] Table E.2 in Internet Appendix E shows that the results are similar when using origination revenue rather than the interest rate. Table E.3 shows that the results are similar when comparing banks to either nonbank-fintechs or nonbank-nonfintechs. Nonbank-fintechs are associated with generally higher interest rates, which could also reflect a premium for greater convenience (Buchak et al., 2018).

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

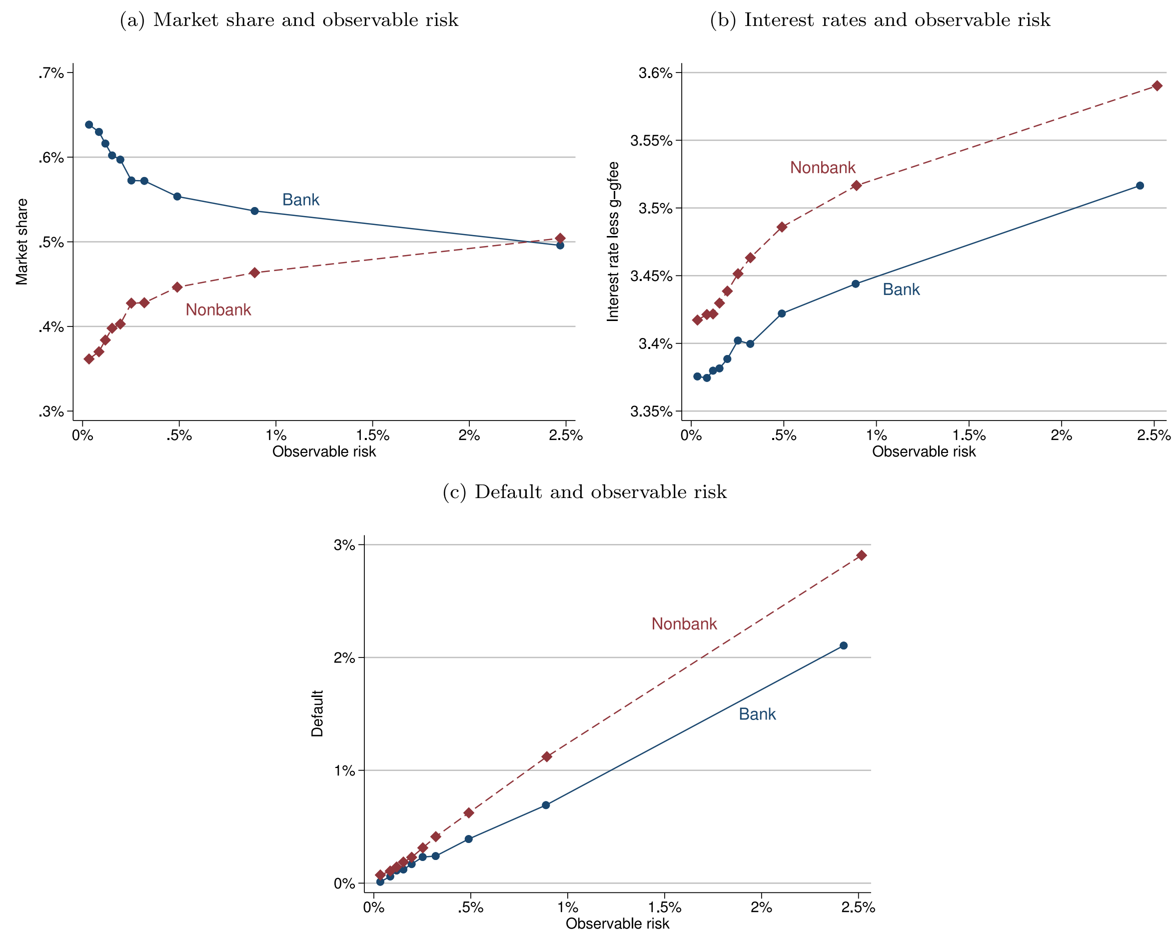

Fig. 7. Empirical comparison of banks and nonbanks.
Fig. 7(a) presents a binned scatterplot of dummy variables indicating whether a loan was sold to the GSEs by a bank or a nonbank on observable risk while controlling for origination year-month fixed effects. These estimates correspond to the respective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

Table 9
Empirical comparison of banks and nonbanks.

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

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

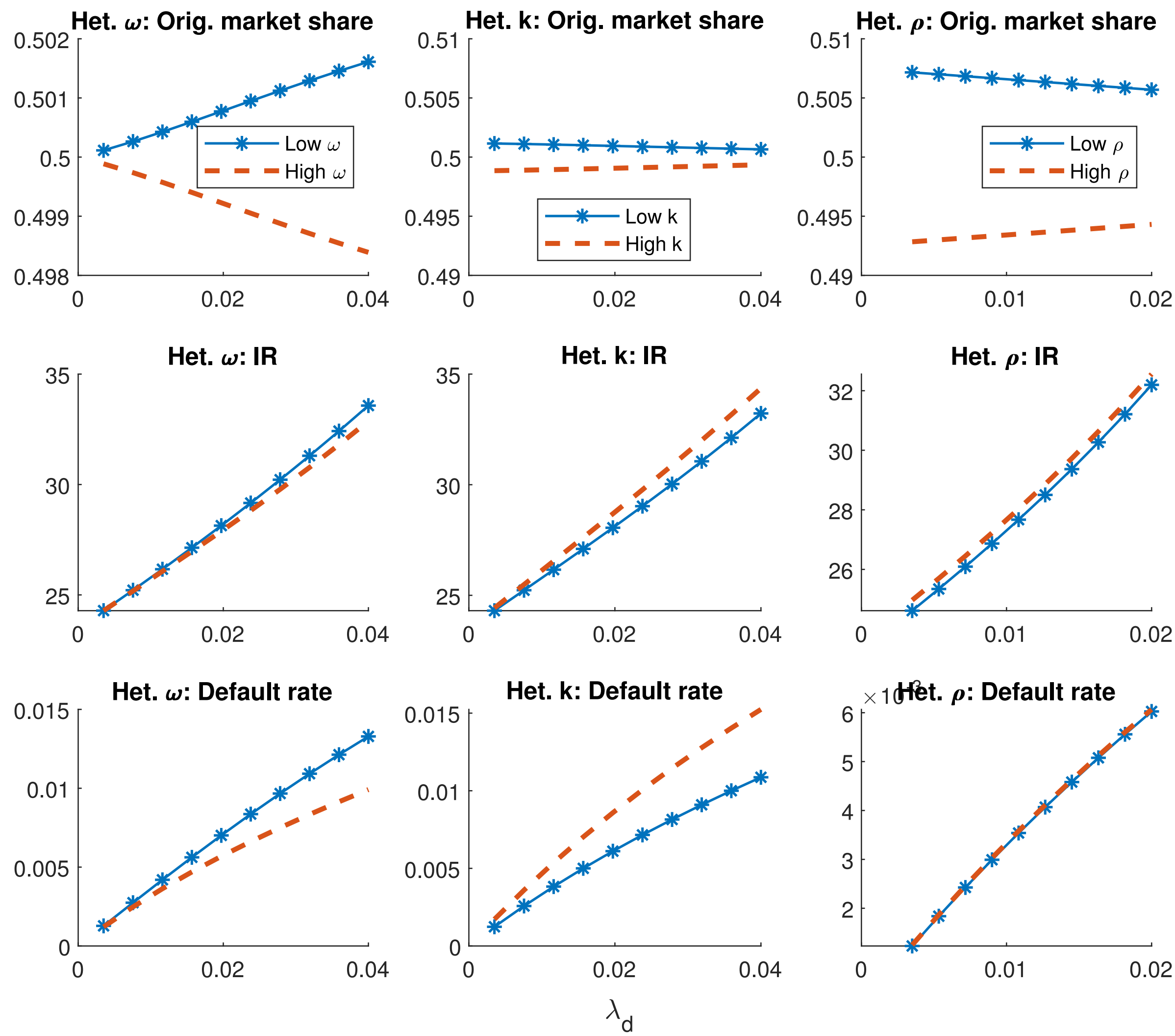

Fig. 8. Comparison of heterogeneous ω, k, and ρ.
These figures show various features of the version of the model with 2 lenders and heterogeneous loss given default ω (left panels), heterogeneous cost of screening k (middle panels), or heterogeneous funding costs (right panels). The *origination market share* refers to the share of originated loans associated with a particular lender. The *interest rate* (IR), which is reported in basis points, is the signal-weighted average interest rate, as described further in Section 4.3. The *default rate* is the fraction of approved applications that consist of defaulting consumers.

magnitude (Buchak et al., 2018) or insignificant (Kim et al., 2022). In particular, we focus on a sample of loans originated in 2016–2017, whereas (Buchak et al., 2018) focuses on loans originated in 2010–2013 and Kim et al. (2022) considers loans originated in 2005–2015. Figure E.3c and Table E.6 in Internet Appendix E show that the association between nonbanks and defaults became more positive from 2013 to 2017.[43]

6.2. Model with heterogeneous lenders

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

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

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

In the case of heterogeneous screening costs, similar to the low loss given default lender in the previous case, the high screening cost lender acquires less information, resulting in a higher default rate. It also has a higher average interest rate to compensate for this risk, which is driven

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

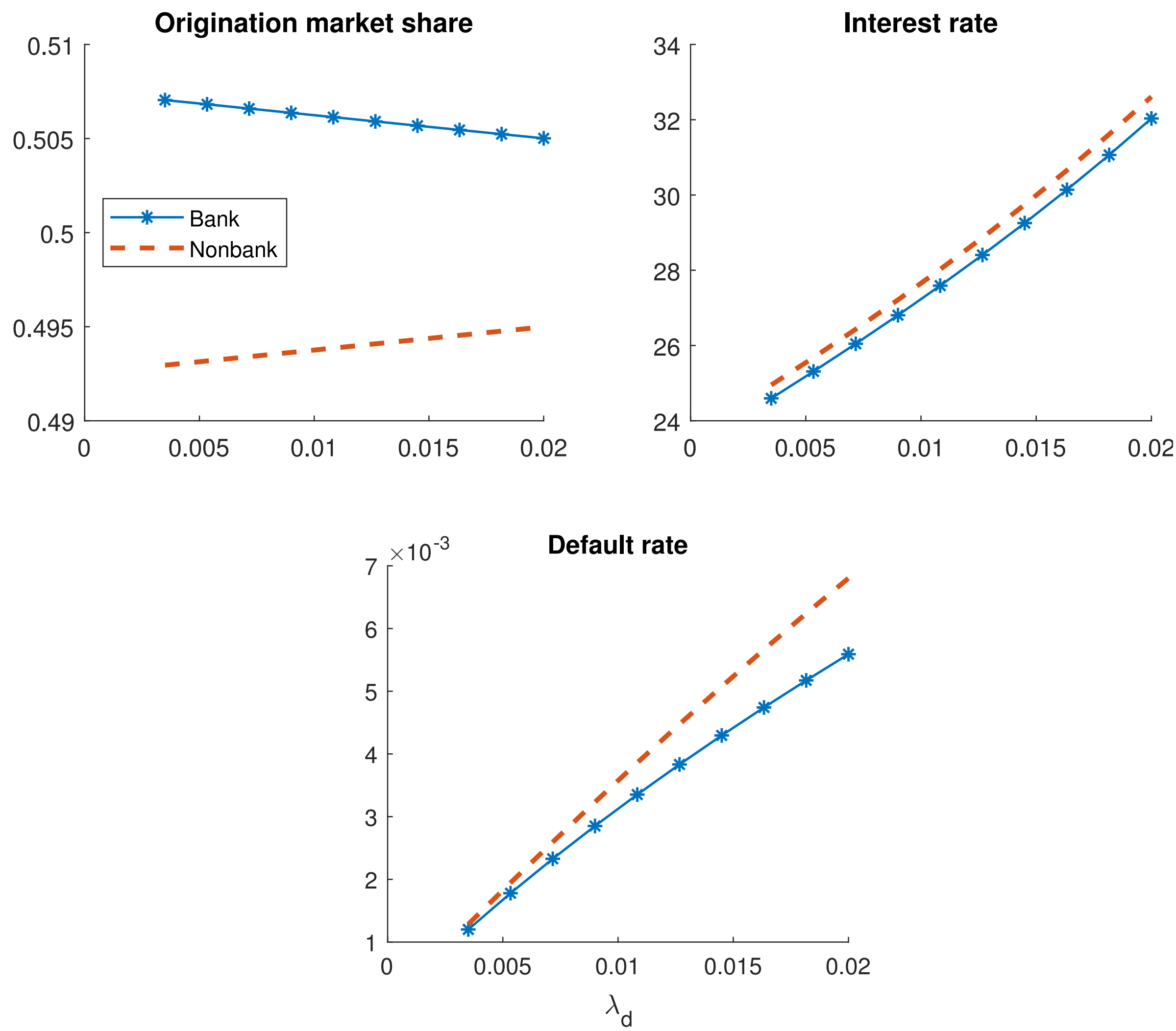

Fig. 9. Model emulation of banks and nonbanks.
These figures show various features of the version of the model with a bank lender and a nonbank lender. The nonbank lender has higher funding costs ρ and lower loss given default ω. The *origination market share* refers to the share of originated loans associated with a particular lender. The *interest rate* (IR), which is reported in basis points, is the signal-weighted average interest rate, as described further in Section 4.3. The *default rate* is the fraction of approved applications that consist of defaulting consumers.

by the fact that a greater fraction of its borrowers have weaker signals. However, conditional on a borrower's signal, the high screening cost lender charges the same interest rate as the low screening cost lender. Therefore, the high screening cost lender lacks an analogous pricing advantage to the low loss given default lender. As a result, even if we select the differences in screening costs to generate a similar difference in the default rate as the case with heterogeneous loss given default, we observe a smaller and opposite overall effect on observable risk, in contrast to Fig. 7(a).

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

Overall, the empirical findings are more consistent with nonbanks having a lower expected loss given default rather than screening costs. This lower expected loss given default could be attributable to nonbanks typically being monolines and therefore having less of a concern to protect profits from other product offerings. The higher interest rates charged by nonbanks even for low risk borrowers is consistent with nonbanks also having higher funding costs. Fig. 9 shows that associating nonbanks with a higher funding cost and lower loss given default qualitatively emulates the empirical observations in Fig. 7.[44] Based on the association between nonbanks and lower funding costs, Figure D.2 in Internet Appendix D suggests that a transition from a market dominated by banks to a market dominated by nonbanks would result in higher default rates. It would also result in relatively lower interest rates for risky borrowers, although the absolute effect on interest rates would also depend on the relative magnitudes of the difference in the loss given default and funding costs.

Figure E.4 in Internet Appendix E further shows that the observed increasing market share and default rates of nonbanks from 2013 to 2017 is consistent with three changes in the model. The first change is a consumer preference shock in favor of nonbanks, which we model by adding a term $A * 1_{\{nonbank\}}$ in the utility (4). This preference shock increases the nonbank market share and interest rate. The second change is a relative reduction in nonbanks' cost of funding ρ, which also increases nonbanks' market share but decreases their interest rates relative to banks. The consumer preference shock and cost of funding

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

shock are jointly determined to significantly increase nonbanks' market share while only slightly increasing their interest rates. Finally, the third change is a relative reduction in nonbanks' loss given default ω, which increases their default rates and leads to a slightly stronger correlation between nonbanks and observable risk.

7. Conclusion

We analyze the trade-offs of how intermediaries shape the origination of GSE mortgages. Specifically, we show that mortgage interest rates net of g-fees increase with observable risk, consistent with lenders independently 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. We estimate the model based on our empirical observations and compare it to a counterfactual effectively without intermediaries. The model shows that intermediaries reduce costs but also charge substantial markups, resulting in higher interest rates, although to a lesser extent for observably risky borrowers.

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

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

CRediT authorship contribution statement

Joshua Bosshardt: Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Ali Kakhbod:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Amir Kermani:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Proof of Eqs. (10) and (11)

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

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

Then the first order condition for r_j^z is

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

Differentiating lender profits as written in Eq. (9) by ψ_j yields

$$\begin{aligned}
0 &= \frac{\partial \Pi_j}{\partial \psi_j} \\
&= s_j^L\left(r_j^L-\rho\right) - (1+q)s_j^M\left(r_j^M(1-\delta^M) - (\rho+\omega\delta^M)\right) - c'(\psi_j) \\
\implies c'(\psi_j) &= s_j^L\left(r_j^L-\rho\right) - (1+q)s_j^M\left(r_j^M(1-\delta^M) - (\rho+\omega\delta^M)\right).
\end{aligned} \tag{A.3}$$

Note that by substituting in r_j^z from Eq. (10), this can also be written as

$$c'(\psi_j) = \frac{s_j^L}{\alpha(1-s_j^L)} - \frac{s_j^M}{\alpha(1-s_j^M)}. \tag{A.4}$$

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