Journal of Financial Economics 162 (2024) 103947

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/finec

Competition, Product differentiation and Crises: Evidence from 18 million securitized loans[☆]

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ARTICLE INFO

Dataset link: Replication Program for "Competition, Differentiation and Crises: Evidence from 18 Million Securitized Loans" (Reference data)

JEL classification:
G01
G2
K2

Keywords:
Securitization
Competition
Product differentiation
Mortgage
Financial crisis

ABSTRACT

RMBS sponsors contributed to the rise of new product features in securitized mortgages prior to the 2008 financial crisis. Using a regulatory shock to sponsor competition , we show securitization influences the design of mortgage contracts, empirically demonstrating a unique, feedback loop of product differentiation from the derived security (MBS) to the underlying asset (loans). Product differentiation in Prime MBS collateral rises faster than that of non-prime in the early boom period (2000–2004), a strategic choice by MBS sponsors in the face of increasing competition. At very high levels of competition, product differentiation targets non-prime (marginal) borrowers. We develop a theoretical framework for sponsor-induced product differentiation that explains these empirical findings.

1. Introduction

In the Schumpeterian view, the introduction of new products by firms drives economic growth (e.g. Kogan et al. (2017)). But, this insight need not extend to *financial* products, given their potential contribution to systemic risk (e.g. Gennaioli et al., 2012, and Judge, 2012). The Global Financial Crisis (GFC) was preceded by extraordinary growth in new products — not only mortgage-backed securities (MBS) but also the underlying collateral. The proportion of private-label securitized loans with interest-only features was around 1.5% in 1999. That number jumped to over 14% in 2004, representing a ten-fold increase. These loans were a key factor that exacerbated the crisis because they performed significantly worse relative to standard mortgages (Amromin et al., 2018). Why was there such a high prevalence of differentiated product features in mortgages in the years preceding the GFC?[1]

Two classes of explanations have been offered so far. On the demand side, Garmaise (2013) and Amromin et al. (2018) attribute this growth to borrower preferences. On the supply-side, Di Maggio et al. (2019) and Acolin et al. (2022) argue that deregulation and originator competition played a role. While important, these explanations are missing a key ingredient — the role of securitization in the issuance

☆ For helpful comments and suggestions, we thank an anonymous referee, Dimitris Papanikolaou (the Editor), Rajesh Aggarwal, Andra Ghent, Benjamin Keys, Adam Levitin, Alexander Reisz, Susan Wachter, Vincent Yao, Elena Loutskina, Anthony DeFusco, Helyoth Hessou, participants at the OCC Symposium on Systemic Risk and Stress Testing in Banking, Financial Innovation: a threat to financial stability Conference of the Federal Reserve Bank of Atlanta and Georgia State University, the Fixed Income and Financial Institutions Conference at the University of South Carolina, Eastern Finance Association Annual Meeting, and seminar participants at Northeastern University. We gratefully acknowledge financial support from the Hans Stoll Financial Market Research Center. All errors are our own.

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[1] We define product differentiation in a mortgage as the inclusion of any of the following non-standard features: balloon payments, interest-only, negative amortization, pay teaser, hybrid and option ARMs. We use this definition in the sense of Thakor (2012), where a differentiated financial product is one that lacks plentiful historical data to accurately assess its risks. The lack of such data makes the financial product harder for competitors to "poach", because there is greater disagreement in the market on its default probabilities.

https://doi.org/10.1016/j.jfineco.2024.103947
Received 18 May 2023; Received in revised form 7 September 2024; Accepted 7 September 2024
Available online 12 September 2024

of non-standard contracts, because an overwhelming proportion of these loans were sold off to MBS issuers ("sponsors"). Even more, mortgage-backed securities themselves became increasingly differentiated (complex) prior to the crisis (Ghent et al., 2017), warranting a closer examination of this period of intense competition in securitization markets. In this paper, we study whether MBS sponsors played a role in the growth of product differentiation in the underlying collateral.

Two aggregate facts suggest such a role. First, the trend in non-standard contracts closely follows the rise and fall of securitization markets (Fig. 1 Panel A). Second, the rise in these features was first observed in the collateral of Prime MBS, a trend that preceded that of non-prime MBS (Fig. 1 Panel B). Neither borrower preferences nor explanations based on lending shocks to originators (such as the 2004 OCC deregulation) can connect these facts.[2] We use novel data on the MBS securitization chain to reconcile these trends and understand how the growth of loan-level product differentiation deepened the financial crisis.

Building on Thakor (2012), we provide a theoretical framework where greater competition between securitization sponsors leads to higher mortgage-level product differentiation. The core idea is that, due to the absence of patent protection, financial institutions have greater incentives to escape competition (á la Aghion et al., 2005), by introducing new products with lower degrees of familiarity because these are less likely to be imitated by competitors. The defining characteristic of a differentiated product in Thakor (2012) is the paucity of historical data that prevents an accurate assessment of its default probability.[3] The theoretical model we develop in this paper adopts this view of product differentiation and studies the incentives of MBS sponsors in a competitive environment. Adding new features to mortgage contracts makes it possible for sponsors to cater to MBS investors as well as enables marginal borrowers – who did not qualify for mortgages offered previously – to take mortgages. Our model generates two empirical predictions. First, increasing competition among MBS sponsors induces originators to issue new contracts to borrowers that are different from existing mortgages. This sequence of events posits a striking *feedback loop* of product differentiation — introduction of a derivative (MBS) can induce changes in the underlying assets (securitized loans). Second, the competitive threshold to warrant such differentiation is lower for higher credit quality loans. Product differentiation brings marginal borrowers into the market, an effect that kicks in only at sufficiently high levels of sponsor competition.

The link between MBS issuers and loan-level product differentiation, however, is hard to establish empirically. It is difficult to ascertain the parent financial institution because MBS are typically issued by special purpose vehicles. Further, increases in sponsor competition may be correlated with unobserved demand for non-standard loans, so the hurdle of identification needs to be overcome. We address these gaps by merging unique, hand-collected data on the SPV's parent company from MBS prospectuses, with detailed information on over 18 million securitized loans from Lewtan's ABSNet. We measure sponsor competition within local markets using a county-level measure ("*Local Sponsor HHI*") defined using the subset of securitized loans made in a given county. We exploit within-state variation in this measure arising from a supply-side regulatory shock that differentially changed competition dynamics for private MBS sponsors. In a dynamic difference-in-differences (DiD) setting, we show that sponsor competition increased heterogeneously in certain areas, leading to a corresponding increase in loan-level product differentiation following the regulatory change.

MBS sponsors are typically financial institutions with a *national* presence. Yet, we find significant cross-sectional and time-series variation in local competition (Fig. 2), a fact that we take advantage of in our empirical tests. What explains this contrast? In RMBS prospectuses, sponsors report the extent of (state-level) geographic diversification in their loan pools, so this constraint induces regional competition among national sponsors. Further, sponsors also report the specific ZIP code with the highest concentration of loans (Internet Appendix Figure IA.B.2), suggesting that sponsors account for the geographic distribution of loans even within a given state. To capture these localized effects, we use a county-level competition measure. Nevertheless, we obtain similar results using broader geographic units of aggregation.

In our baseline tests, we document an economically significant link between increases in MBS sponsor competition and the probability of a loan having a non-standard feature. A one standard deviation decrease in local sponsor HHI results in an increase of 1.2–2.5 pps. in the probability of loan-level product differentiation, translating into a 2.6–5.4 percent relative increase in the likelihood of differentiation. To the best of our knowledge, this result is the first evidence of a feedback loop where issuance of a differentiated derived security can induce such features in the underlying assets. While Back (1993) provides a theoretical analysis of such a phenomenon in options markets, there has been no empirical evidence supporting it thus far.

Our baseline tests include fixed effects that account for time-varying regulatory shocks at the state-level. For instance, our results cannot be explained by differences in originator responses to the 2004 preemption rule across states with variation in anti-predatory lending laws (Di Maggio et al., 2019). We compare loans across demographically-similar counties with comparable borrower demand for mortgage loans. By using fixed effects at the sponsor level, we also account for a predisposition for risk-taking that was prevalent among certain sponsors (such as Countrywide) during the pre-crisis period. Even so, loan contracts are offered by originators and not by the sponsors themselves. What if the issuance of differentiated loans was a response by originators to local demand conditions? To address this concern, we exploit the data's granularity to test for differences in outcomes *from the same originator*, in the same region and year, but that are exposed to different levels of sponsor competition. This empirical strategy uses fixed effects to restrict variation *within* the same Originator × State × Year, accounting for time-varying confounds at the originator level. We continue to find robust results with a more stringent restriction on local time-varying unobservables at the Originator × CBSA × year level. The within-originator analysis provides credence to our claim that MBS sponsors played a role in product differentiation of the underlying collateral.

While fixed effects can shut down confounding sources of variation, they are less useful in isolating an identifying source of variation in MBS sponsor competition that is plausibly exogenous. In the absence of such variation, we may worry about reverse causality — suppose higher borrower demand for differentiated mortgages created more high-margin opportunities for securitizers, then such demand may have attracted new sponsors to enter, increasing competition among them.[4] To this end, in our main identification strategy, we study a regulatory

[2] Prior research has argued that subprime credit expansion was fueled by securitization, but product differentiation is outside the scope of these analyses (Mian and Sufi, 2009; Nadauld and Sherlund, 2013). On the other hand, securitization is outside the purview of research on the prevalence of complexity in the prime segment (Garmaise, 2013; Amromin et al., 2018). For instance, when loans with non-standard features are offered by an originating bank, Garmaise (2013) shows that risky borrowers adversely select into such features. Whether securitization markets themselves induce originating banks to offer such contracts to borrowers remains unclear.

[3] In the early 2000s, non-standard features introduced into the collateral of private label MBS lacked historical precedence (Internet Appendix Figure IA.B.1).

[4] To the extent the level of mortgage applications in a given area reflects borrower demand, we are already controlling for that factor. Further, our fixed effect structure (Originator × CBSA × Year) already controls for time-varying demand conditions at a high level of granularity. Nevertheless, it is challenging to rule out confounding factors in the absence of an exogenous source of variation.

(a) Why is sponsor activity connected to loan differentiation? (b) Why does prime differentiation precede that of non-prime MBS in the early boom period?

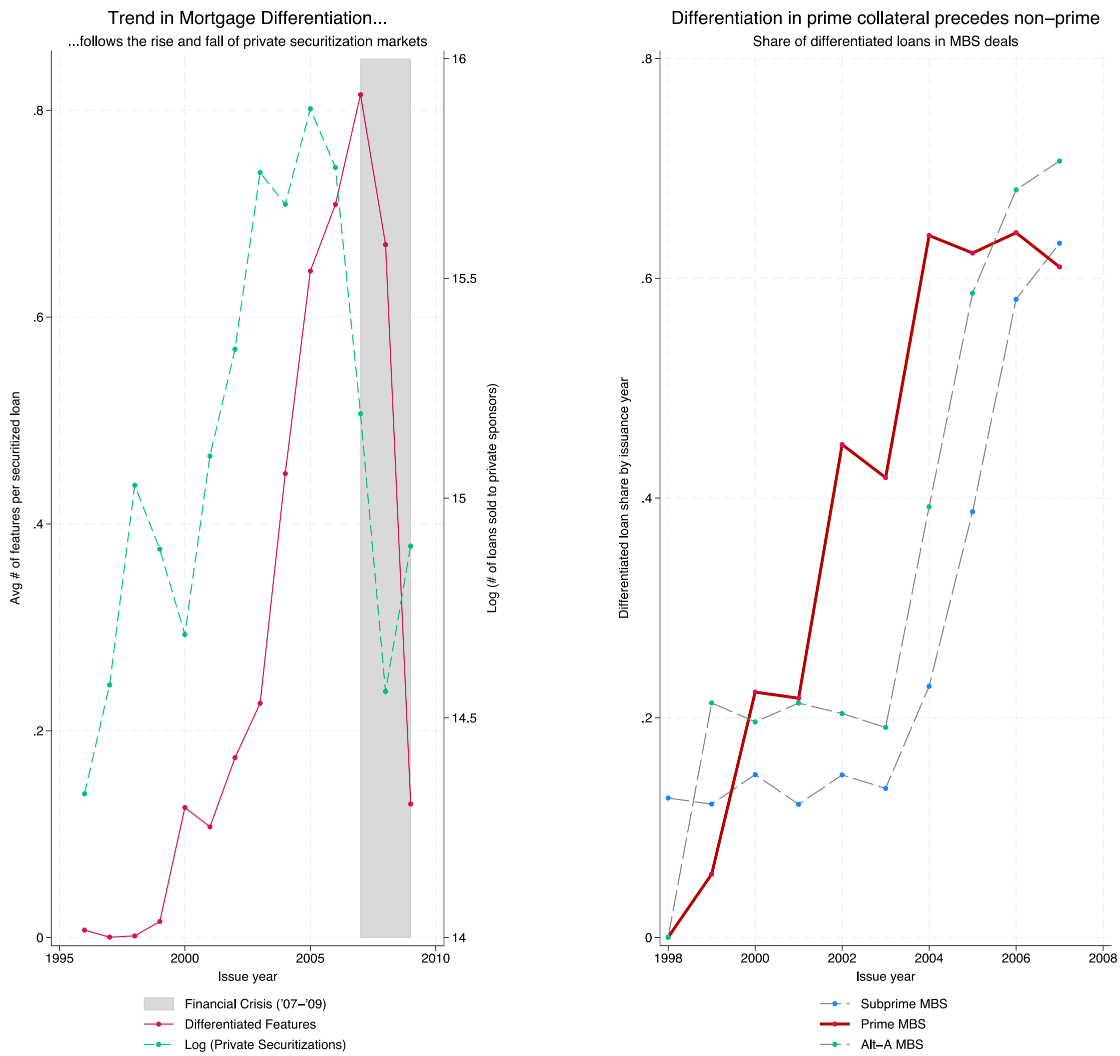


Fig. 1. Puzzling trends in the evolution of non-standard mortgages. This figure lays out two open questions: (a) why is activity in private securitization markets correlated with loan-level differentiation? and (b) why does the rise of differentiation in prime MBS collateral precede that of non-Prime collateral? The aggregate evolution of non-standard mortgages in RMBS securitization markets is tracked using a comprehensive database of over 18 million loans. In both panels, the x-axis is the year in which the loan was securitized (i.e. the year of closing of the securitization deal). The dashed line (left axis) of Panel (a) counts the average # of non-standard features per securitized loan. The timing of this growth coincides with the number of loans sold to private securitizers plotted in the solid line (right axis). This data comes from the HMDA disclosure on loan purchases. In Panel (b), we show the varying rates of differentiation by type of MBS. We use the deal classification from the ABSNet database to categorize these types. Private securitizers used more non-standard features in Prime MBS relative to non-prime MBS such as Subprime and Alt-A in the early 2000s. Differentiation refers to mortgages having non-standard features: Hybrid ARM, Balloon, Interest Only, Negative Amortization, Pay Teaser, and Option ARMs.

change affecting securitization competition, and trace out the effects of this shock on mortgage-level product differentiation. In 2000, the affordable housing goals of the Housing and Urban Development (HUD) required Government-Sponsored Enterprises (GSE's) to significantly increase securitization in low-income areas relative to high-income areas.[5] We implement the effect of this rule in a dynamic difference-in-differences (DiD) setting. Similar to the "crowding out" effect shown in Gabriel and Rosenthal (2010), we find that the entry of GSE's into underserved regions had the unintended effect of encouraging private securitizers to compete more in the high-income areas. As a result of the sudden increase in private sponsor competition, we show non-standard features significantly increased in those counties, providing compelling evidence of the role of sponsors in inducing differentiation in the underlying collateral. Supporting a causal interpretation, our dynamic DiD regressions exhibit parallel trends in the pre-period, ruling out the possibility that outcomes in treated and control counties had differential trends prior to the regulation.

As we moved closer to the financial crisis, non-standard features became more common, leading sponsors to seek alternative ways to differentiate themselves even more. At very high levels of competition, our theoretical model predicts that these features were offered to marginal (non-prime) borrowers. To test this hypothesis, we use two splines of our HHI measure based on the degree of competition (SponsorHHI^{low} and SponsorHHI^{high}). When we interact these two measures with borrower quality, we find both the propensity and intensity of product

[5] The rule used census tracts to defined underserved areas. A census tract qualifies as an underserved area if its median family income is 90% or less than the median income of the corresponding MSA. We compute the proportion of underserved census tracts in a county and classify counties in the 75th (25th) percentile as low (high) income counties.

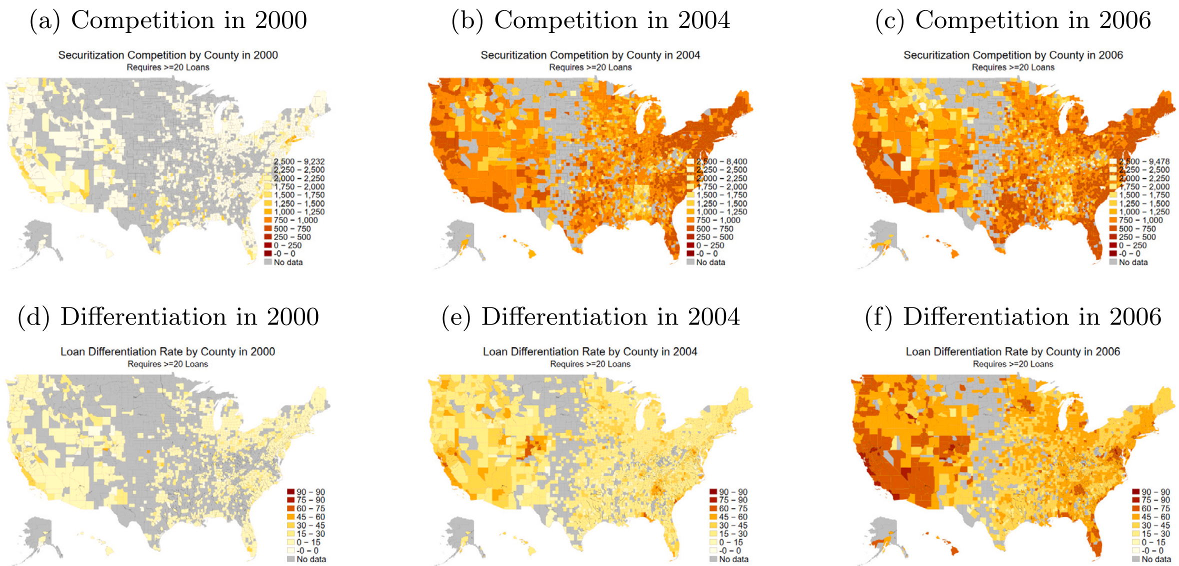


Fig. 2. The localized nature of sponsor competition. This figure shows snapshots of geographic dispersion in sponsor competition (scaled) and loan differentiation for three time periods prior to the crisis (years 2000, 2004, and 2006). We see significant dispersion in local sponsor competition that we exploit in our regression analysis. Further, a comparison of the top and bottom panels suggest sponsor competition leads the growth in loan differentiation. The graphs are plotted using the full sample of securitized loans from ABSNet.

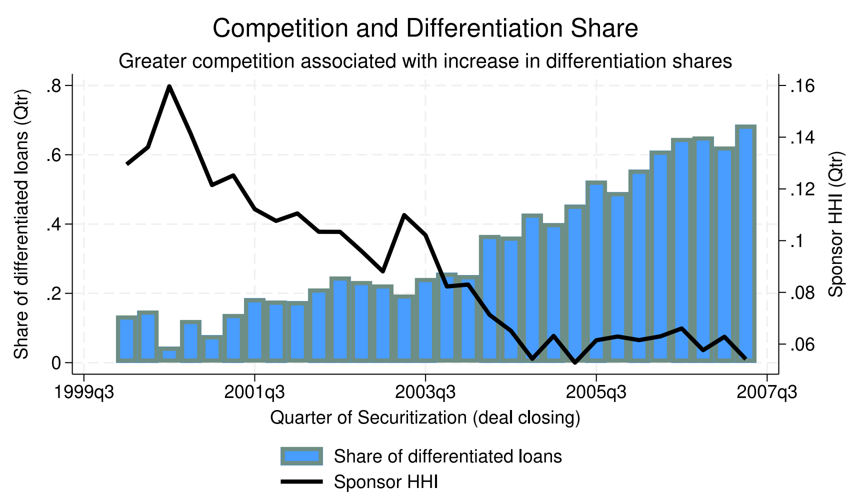


Fig. 3. Greater sponsor competition is associated with higher loan-level differentiation. This figure tracks the aggregate relation between differentiated loan prevalence and sponsor competition (measured using the Herfindahl–Hirschman Index (HHI)). A higher value of Sponsor HHI indicates a lower level of competition among sponsors. On a quarterly basis over time, we plot the share of differentiated loan features (bar charts, left-hand axis) and Sponsor HHI (solid line, right-hand axis). As sponsor competition increases (decrease in Sponsor HHI), we see an increase in the share of differentiated loans over all loans securitized during this period. The average rate of mortgage differentiation in the sample is 46%.

differentiation is greater for marginal borrowers, but only at high levels of competition. Using HMDA data, we also find that mortgage application denial rates are lowest for areas with more marginal borrowers when facing high levels of sponsor competition. Our evidence suggests that sponsor-induced product differentiation expanded the borrower pool to the marginal segment in the years immediately preceding the crisis.

Prior research has shown evidence of obfuscation by sponsors — complex MBS products defaulted at a greater frequency than standard MBS, and investors did not perceive differentiated products offered by sponsors as being riskier, ex-ante (Ghent et al., 2017). We find corroborating evidence at the loan-level that is consistent with this notion. Over $190 billion of differentiated loans packaged into low-yield, prime MBS during 2000–2008 subsequently became delinquent. In the early boom period (2000–2004) coinciding with sponsor-induced product differentiation, the delinquencies of differentiated prime loans was large ($91 bn), even relative to similar cohorts in Subprime ($24.5 bn) and Alt-A ($16.2 bn) collateral. This pattern reversed in the later part of the sample, with delinquencies being highest in the marginal borrower segment just before the crisis. These results provide suggestive evidence that competition-induced differentiation led to greater risks that deepened the financial crisis.

The intended marginal contribution of this paper is threefold. To begin, we provide the first empirical support for the theoretical predictions of Back (1993), namely that the introduction of a derivative affects the pricing dynamics of the underlying asset.[6] In our context, competition among issuers of the derived security (MBS) induces product differentiation in the underlying assets (securitized loans). These results raise an interesting challenge for future theoretical models on

[6] Although one could argue that the precise product differentiation-based mechanism in our argument differs from the trading-based mechanism in Back (1993).

MBS security design because we show that securitization itself can influence the design of mortgage contracts.

Second, we document new facts on the role of securitization in the differentiation of mortgage collateral. Our results reconcile two seemingly unconnected strands of the literature — the prevalence of complex features in loans made to *higher* income households (Amromin et al., 2018) with the role of securitization in fueling *subprime* mortgage credit expansion (Mian and Sufi, 2009; Nadauld and Sherlund, 2013). Competition-induced product differentiation not only led to the greater prevalence of non-standard features in the prime segment, but these features also expanded to borrowers of marginal credit quality at very high levels of competition. While the financial crisis literature has argued a role for securitization in the expansion of subprime mortgage credit, it has largely remained silent on the product differentiation margin, a gap that our evidence fills.

Third, we contribute to the debate on how incentives of financial institutions contribute to financial crises. Given that non-standard mortgages performed significantly worse relative to standard products, our results point to a potential risk build-up that arose from sponsor competition. With the well-documented spillover costs of default, this begs the question as to what extent sponsor-induced product differentiation exacerbated the 2007–09 financial crisis. Since MBS investors did not fully anticipate risks at the time, our results also suggest that greater differentiation potentially facilitated obfuscation. Thus, we complement the finding in Ghent et al. (2017) by showing that obfuscation may have extended beyond MBS design, to the sourcing of the collateral underlying these products.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 develops the theoretical model. Section 4 discusses the data and the measurement of sponsor competition. Empirical evidence is presented in Sections 5, 6, and 7. Section 8 presents robustness checks. All proofs are in the Internet Appendix A.

2. Related literature

Our paper complements earlier research on competition among originators and their role in the complexity of subprime mortgages. Di Maggio et al. (2019) study the 2004 OCC preemption rule, and provide evidence that this deregulation led non-OCC lenders to issue non-standard loan contracts via an indirect competition channel, in states not restricted by anti-predatory lending (APL) laws. Acolin et al. (2022) also find APL laws helped to reduce the effect of concentration on non-standard mortgages. Our focus is on the effect of *sponsors*, rather than originators, so the securitization pipeline is central to our setting. We analyze growth in these contracts in the early 2000s, so the economic forces in our setting operate several years prior to the 2004 shock affecting mortgage originators. While the increase in credit supply due to the OCC rule targeted the subprime borrower segment, we show growth in non-standard features occurring in prime borrowers as a result of a regulatory shock affecting the securitization of GSE loans. Levitin and Wachter (2020) argue that the pre-crisis housing bubble resulted from a supply glut driven by private-label securitization. In their view, nontraditional mortgages enabled the expansion of the borrower pool, a premise for which we find supporting evidence in the paper. Consistent with this supply-side story, Dokko et al. (2019) find increased product differentiation preceded non-fundamental house price growth and was accompanied by a decline in denial rates. Our paper contributes to this work by highlighting the role of private sponsors in driving product differentiation in mortgage contracts.

Our work is related to Gabaix and Laibson (2006) who present a model of obfuscation (the process of sellers shrouding product attributes to increase buyer search costs) that can persist in competitive markets. In the securitization context, Ghent et al. (2017) provide evidence consistent with sponsor incentives to obfuscate MBS products through complexity at the deal structure level. Such strategic decisions by sponsors to increase investor search costs, can plausibly extend to the underlying collateral of the MBS themselves. But direct evidence on such a mechanism has been lacking so far. To our knowledge, we are the first to show a direct link between MBS sponsor competition and financial product differentiation in the underlying mortgage collateral. Our results on distress of low-yield prime MBS collateral provide evidence on emerging theoretical work on obfuscation (Spiegler, 2016).

The financial crisis literature has shown securitization weakens lender incentives for screening (Keys et al., 2010; Purnanandam, 2011; Griffin and Maturana, 2016; Vanasco, 2017; Ashcraft et al., 2019). We expand on this literature by showing cross-sectional differences in loan performance within the universe of securitized loans. Conditional on a loan being securitized, we show that non-standard mortgages performed worse than standard mortgages. Further, the differentiated mortgages in low-yield MBS fared worse than those in higher-yield MBS for loans securitized during the boom years. Our results explain the role of competition in precipitating financial crises, building on Thakor (2012) where competition prompts product differentiation, which then heightens disagreement in asset valuations and increases the likelihood of funding disruptions. Our study of competition among securitizers complements the empirical work in Berger et al. (2017) who study linkages between bank competition and financial stability.

Prior research has investigated borrower demand in explaining the rise of non-standard features (e.g., Piskorski and Tchistyi, 2010; Cocco, 2013). Amromin et al. (2018) document a significant jump in complex mortgage defaults, focusing on the role of contract design. They find complex mortgages are used by higher-income households rather than by subprime borrowers. Our results point to a sponsor competition channel, offering a new explanation for why non-standard mortgages grew in the early 2000s. Using the 2000 HUD Affordable Housing Act that affected GSE purchases, we also shed light on why this growth initially focused on the prime segment.

Our results extend the line of research on product complexity decisions. Asriyan et al. (2023) develop a model in which greater investor demand leads to more complex and possibly lower-quality products. Thakor and Merton (2023) develop a theory of product complexity and information disclosure in which complexity adds value but increases the cost of disclosure, and in equilibrium the producers of the most complex products disclose the least information. The strategy of MBS sponsors to "escape the competition" by differentiating is consistent with the theory in Carlin (2009), who argues that complexity increases the market power of firms. Krieger et al. (2022) find evidence that non-financial firms innovate when faced with negative shocks to existing products. Célérier and Vallée (2017) provide evidence that financial complexity in MBS products arises from the need to cater to yield-seeking investors. We provide a theoretical foundation and empirical evidence that such catering incentives can even filter into the underlying mortgage collateral. Our results imply MBS sponsors can themselves influence the design of the underlying collateral backing such products. Thus, our empirical evidence presents a challenge to traditional theoretical models on security design. For example, what is the role of competition among the issuers of derivative securities driving differentiated features in the underlying assets on which these derivatives are written? This question has relevance far beyond mortgages and MBS to a wide range of financial contracts.

3. Theoretical framework

In this section, we present a theory model that builds on Thakor (2012) to motivate the connection between MBS sponsor competition and product differentiation. The model's main goal is to explain the economics of why competition among sponsors in the securitization market leads to mortgage-level product differentiation.

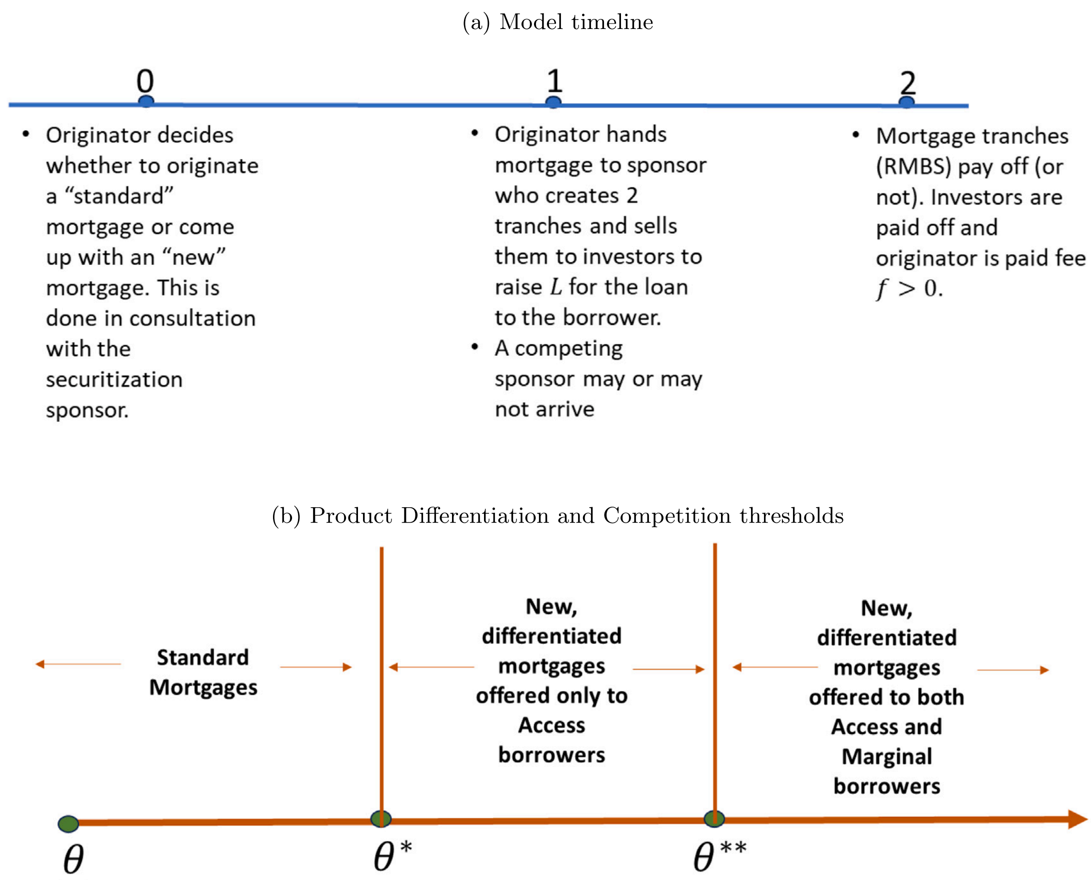


Fig. 4. Model timeline and competition thresholds. Panel (a) of this figure shows the sequence of events for the theory in Section 3. Panel (b) shows the relation between product differentiation, competition thresholds, and marginal borrowers. θ refers to the probability of competitive entry.

3.1. Model

Consider an economy with universal risk neutrality and a zero riskless rate. There are the following main players in the model: a borrower seeking a mortgage, an originator who originates the mortgage and "designs" it, a securitization sponsor who provides the funding for the mortgage by selling tranches to investors, and investors who buy these tranches. The sequence of events is outlined in Fig. 4. There are three dates. The model begins at Date 0 when the originator, in consultation with the sponsor, must decide whether to issue a "standard" or "new" (product-differentiated) mortgage. The sponsor is then responsible for selling at Date 1 when a competing sponsor may or may not arrive. At Date 2, investors receive their payoffs.

Originator and Sponsor: We assume there is never any disagreement or conflict of interest between the sponsor and originator about payoff values. The originator (e.g. bank) simply collects a fee $f > 0$ (stipulated exogenously) for originating (and possibly servicing) the mortgage for a borrower who needs to borrow L. The sponsor then securitizes the mortgage, creating 2 tranches and selling them to investors.

Competition in the Securitization Market: We take the market structure in the mortgage origination market as given, so the borrower agrees to a repayment equal to all of his pledgeable future cash flow in exchange for a loan of L at $t = 0$. The repayment occurs at $t = 2$.

In the securitization (RMBS) market, sponsors compete for investors to sell their tranches to. We assume that there is a probability $\theta \in (0, 1)$ that a competing sponsor will arrive. In this case, the two sponsors engage in Bertrand competition and each earns zero expected profit if they are successful in selling the tranches to investors — this is net of the fee f paid to the originator.

If investors do not buy both the tranches, then L cannot be raised and the borrower will *not* take the mortgage (i.e., the loan request is indivisible). However, the sponsor still has to pay the originator f, so the sponsor suffers a loss of f (profit$= -f$) if both tranches do not sell.

Payoff on Primary Mortgage: There are two types of borrowers: those with regular access to credit ("access" borrowers) and those without ("marginal" borrowers). For now, we will focus on access borrowers, and describe marginal borrowers later. There are two types of mortgages. The standard existing mortgage (designated by the subscript "o" for "old") allows the access borrower to borrow L and get a payoff of:

$$z_o = \begin{cases} X + Y & \textit{with probability } \; p_o \in (0,1) \\ x + Y & \textit{with probability } \; 1 - p_o \end{cases} \tag{1}$$

where X is the access borrower's pledgeable payoff (say disposable income + savings from not paying rent) in the "good" state (full employment) and x is the pledgeable payoff in the "bad" state (unemployed or only partially employed), with $0 < x < X$.

$Y > 0$ is the access borrower's nonpledgeable income/utility. This could be joy of ownership of the house plus cash income that the bank cannot contract upon. Since $Y > 0$, the borrower wants the mortgage even if the repayment equals all pledgeable cash flow.

For the access borrower, the new mortgage (with subscript "n" for "new") has a payoff structure:

$$z_n = \begin{cases} X + Y & \textit{with probability } \; p_n \in (0,1) \\ x + Y & \textit{with probability } \; 1 - p_n \end{cases} \tag{2}$$

Since the new mortgage has no prior data on repayment etc., agents form "rational beliefs", in the sense of Kurz (1994), about p_n (see Thakor, 2012). The originator draws p_n from $\{p, 0\}$ where $p \in (0, 1]$.

If $p_n = 0$ is drawn, the originator discards the new mortgage idea. So we focus only on the case in which the originator draws $p_n = p$. Assume:

$$L > x > f \tag{3}$$

$$p_o X > L \tag{4}$$

$$pX > L \tag{5}$$

There is some uncertainty about the access borrower's willingness to use a new mortgage. Let $\Psi \in (0, 1)$ be the probability that a new mortgage will be accepted by an access borrower.

***Disagreement and Competition in the Securitization Market*:** Let ρ be the degree of innovation or newness in the new mortgage. The higher ρ is, the more differentiated the new mortgage is, i.e., the greater its difference compared to the old mortgage. Let $\rho \in [\underline{\rho}, \overline{\rho}]$.

The basic idea here, based on Thakor (2012), is that a greater paucity of historical data leaves more room for agents (with heterogeneous priors) to come up with different posterior beliefs about the payoff distribution of a loan. As Kurz (1994) showed, when the underlying state variables are drawn from non-stationary distributions, the rational posterior beliefs of agents – all of whom observe the same data – can diverge. New types of loans will have less historical data on them than traditional loans that have been in the market for a long time. Traditional loans will thus have a sufficiently long time series of data to enable differences in posterior beliefs to narrow, but this will typically not be the case for new types of loans. So we view a loan as more differentiated if there is less historical data on its performance.[7]

Let $q(\rho)$ be the probability that a competing sponsor will agree that the new mortgage is worth securitizing — i.e., $q(\rho)$ is the probability that a competing sponsor will also draw $p_n = p$. We assume:

$$q' < 0, \quad q'' = 0 \tag{6}$$

i.e., the probability of agreement with more differentiated mortgages is lower. This is because the newer and more differentiated a security, the higher is the likelihood that competitors will disagree about whether it is an attractive security to imitate. For simplicity, we assume q is linear. Assuming a non-linear q function adds algebraic complexity without adding insight.

Similarly, let $S(\rho)$ be the probability that investors will also draw $p_n = p$. We assume:

$$S' < 0, \quad S'' < 0 \tag{7}$$

with the Inada conditions $S'(\underline{\rho}) = 0, S'(\overline{\rho}) = -\infty$.

In general, we could make $p_n(\rho)$ a function of ρ, say $p_n(\rho) = p_o + r(\rho)$ with $r' > 0, r(0) = 0$. This would naturally link the old and new mortgages, so $\rho = 0$ would imply both are the same ($p_n = p_o$). But for simplicity, we assume that $\rho \in [\underline{\rho}, \overline{\rho}]$ is the feasible set of ρ, and p_n is unaffected by ρ. Thus,

$$1 > q(\underline{\rho}) = \underline{q} > q(\overline{\rho}) = \overline{q} > 0 \tag{8}$$

We do not impose any restriction on what the relationship of p is to p_o, although $p > p_o$ is a natural assumption.[8]

[7] It is true that in other international settings, borrowers were more reliant on adjustable rate features. But extrapolating default risk data of borrower pools from other countries into the U.S. may have been challenging for investors. Also, beyond adjustable rate mortgages, we include loans that are interest-only, reverse mortgages, and option ARMs in our definition, which are less prevalent features in an international context.

[8] Although we do not model competition among originators for borrowers, our specification is consistent with a frictional (random) search model in which borrowers and originators search and match and the payoff structure is determined through Nash bargaining. Also, there is no disagreement with standard (old) mortgages.

***Marginal Borrowers*:** The marginal borrower's payoffs from the standard and differentiated mortgages (with the superscript "m" to designate "marginal") are:

$$z_o^m = \begin{cases} X + y & \text{with probability } p_o^m \\ x + y & \text{with probability } 1 - p_o^m \end{cases} \tag{9}$$

$$z_n^m = \begin{cases} X - [\hat{\rho} - \rho]y & \text{with probability } p_n \\ x - [\hat{\rho} - \rho]y & \text{with probability } 1 - p_n \end{cases} \tag{10}$$

where $y > 0$ is a non-pledgeable payoff to the borrower and $\hat{\rho}$ is a threshold level of differentiation in the mortgage. We assume

$$p_o^m X + [1 - p_o^m]x < L \tag{11}$$

The interpretation of these expressions is as follows. Eqs. (9) and (11) jointly imply that the marginal borrower does not qualify for a standard mortgage. Expression (10) says that the marginal borrower will not apply for a new type of mortgage as long as the newness in the mortgage is less than some threshold level, $\hat{\rho}$. What we have in mind is that a mortgage would have to be sufficiently differentiated in terms of its design to induce marginal borrowers to simultaneously apply and also be creditworthy. But, if this condition is satisfied, a marginal borrower will take the new mortgage with probability 1. For simplicity, we assume that a lender will approach a marginal borrower only if an access borrower cannot be found for the new mortgage.

***Securitization*:** The sponsor splits the mortgage into two tranches. Tranche 1 is most senior and is guaranteed a payoff of $x - f$, while tranche 2 is riskier and is promised $z - x$. Thus, tranche 2 receives a payoff of $X - x$ in the "good" state and nothing in the "bad" state. The originator is promised f. Thus, the distribution of payoffs is:

Payoffs

$$= \begin{cases} \text{Originator:} & f \quad \text{with probability } 1 \\ \text{1st tranche:} & x - f \quad \text{with probability } 1 \\ \text{2nd tranche (residual):} & \begin{cases} X - x & \text{with probability } p_o \text{ or } p_n \\ 0 & \text{with probability } 1 - p_o \text{ or } 1 - p_n \end{cases} \end{cases} \tag{12}$$

Analysis with access borrowers

Our analysis initially focuses on access borrowers exclusively. We introduce marginal borrowers later.

Proposition 1. *If the sponsor securitizes a standard (old) mortgage, the securitization always succeeds and the expected profit of the sponsor is:*

$$\Pi_0 = [1 - \theta]\{p_o X - L + x - f\} \tag{13}$$

Proof. See Internet Appendix A.

Proposition 2. *Suppose an access borrower takes a new, differentiated mortgage. Then, the securitization fails with probability $1 - S(\rho)$. The expected profit of the sponsor is:*

$$\Pi_n = \begin{cases} [1 - \theta q(\rho)]\{S(\rho)[pX - L + [x - f]] + [1 - S(\rho)][-f]\} \\ -\theta q(\rho)\{f[1 - S(\rho)]\} \end{cases} \tag{14}$$

There exists a unique optimal degree of differentiation, $\rho^* \in (\underline{\rho}, \overline{\rho})$.

Proof. See Internet Appendix A.

Proposition 3. *Assume originators are extending mortgages to access borrowers. There exists a probability θ^* such that when the probability of competitive entry θ exceeds θ^*, the sponsor prefers the (optimal) new mortgage over the standard mortgage. Given a small enough f, $\theta^* \in (0, 1)$.*

Proof. See Internet Appendix A.

Analysis with access and marginal borrowers

Now we allow marginal borrowers to be in the credit market. As indicated earlier, these borrowers do not qualify for standard loans, and they enter the analysis only if the lender cannot find an access borrower to take a new, differentiated mortgage.

Proposition 4. *When there are both access and marginal borrowers in the credit market, the optimal degree of product differentiation with the new mortgage, ρ^*, is increasing in the degree of competition, θ. The sponsor prefers the (optimal) new mortgage over the standard mortgage when the probability of competitive entry, θ, exceeds some threshold level, θ^*. Moreover, for $\hat{\rho}$ high enough, mortgages are offered to marginal borrowers only when competition $\theta > \theta^{**} > \theta^*$.*

Proof. See Internet Appendix A.

This proposition indicates that there are two forces at work in generating the impetus for product differentiation in mortgages, and both are related to competition among sponsors. As competition increases, the *expected* profitability of standard mortgages declines, and at a sufficiently high level of competition, the new mortgage is preferred by the sponsor. So this is the first force. The second force kicks in when competition rises further and ρ^* rises so that it now exceeds $\hat{\rho}$, thus making the new mortgage attractive for marginal borrowers. This is depicted in the Panel (b) of Fig. 4.

3.2. Predictions

Propositions 1–4 generate two empirical predictions:

Prediction 1: Greater sponsor competition leads to a higher probability of a loan having a differentiated feature.

Prediction 2: As competition increases, differentiated loan features are first observed among prime borrowers. At higher levels of competition, product differentiation targets marginal borrowers. Marginal borrowers are associated with greater degree of differentiation.

4. Data and summary statistics

Our data comes from multiple sources. Securitized residential mortgages from ABSNet is provided by Lewtan, a Moody's Analytics Company. We merge this database with county-level information on loan applications (HMDA), originator-servicer information (Bloomberg), county-level demographics (Bureau of Economic Analysis) and underserved census tracts from Bhutta (2012). After dropping observations with missing information, we are left with 18 million loans from metropolitan areas covering the period 1997 to 2008.

A novel feature is that we hand-collect information linking the special purpose vehicle (SPV) issuing the MBS to the parent sponsor by searching individual MBS prospectuses. Thus, our data allows us to track the ultimate sponsors as they securitized loans through space and time. Internet Appendix Table IA.B.1 shows a sample matching of issuer SPV's to the parent sponsor (Panel (a)). The largest sponsors, by value of loans securitized, include Countrywide, GMAC, Lehman Brothers, and Bear Stearns (Panel (b)).

Table 1 provides details on loan characteristics by property type (Panel (a)), loan purpose (Panel (b)) and type of MBS (Panel (c)). The number of loans in each category and the average loan size are split by whether a loan is standard or differentiated. We define a loan as differentiated if it has one or more of the following features: Hybrid Adjustable Rate Mortgages (ARMs), Balloon Payments, Interest Only, Pay Teaser, Negative Amortization, Option ARMs. Our main dependent variable is an indicator that turns on if a given loan j in county c in year t is classified as differentiated ($\mathbb{1}_{\text{Differentiation}_{j,c,t}}$). In later tests, we define the degree of differentiation as the number of features the mortgage contains. These features fit a common description of non-standard or complex loans in that they backload mortgage payments which allows for lower payments upfront, as compared to fully amortized loans (Garmaise, 2013; Amromin et al., 2018).

Most loans in our sample are single-family homes, with the mean balance at loan origination being \$199,788 for standard loans. Differentiated loans are larger (\$283,221) suggesting that they are likely associated with higher income borrowers (Amromin et al., 2018). Panel (b) of Table 1 shows that the most common category for both standard and differentiated mortgages are purchase loans. In terms of the type of MBS these loans are securitized into (Panel (c)), we find that a majority of loans in our data form part of subprime MBS (≈9.4 mn), relative to prime MBS (≈3.4 mn) and Alt-A MBS (≈3.6 mn). Differentiated loans, however, form a slightly greater proportion of prime MBS (≈1.8 mn) relative to standard loans in the prime category (≈1.6 mn).

4.1. Measuring sponsor competition

We measure local sponsor competition for the N sponsors sourcing loans in county c in year t as follows. Let $LoanBalance_{i,j,c,t}$ represent the loan amount at origination of loan j securitized by sponsor i. If $M_{i,c,t}$ is the total loans made by a sponsor in a given county-year, then the market share of sponsor i in county c in year t is defined as:

$$s_{i,c,t} = \frac{\sum_{j=1}^{M_{i,c,t}} LoanBalance_{i,j,c,t}}{\sum_{i=1}^{N} \sum_{j=1}^{M_{i,c,t}} LoanBalance_{i,j,c,t}} \tag{15}$$

Using these market shares, we construct our Herfindahl index at the county-year level:

$$\text{LocalSponsorHHI}_{c,t} = \sum_{i=1}^{N} s_{i,c,t}^2 \tag{16}$$

The county-year level is broad enough to capture the time trend while avoiding seasonality or any distortions from large issuances in a particular quarter. Our results are not sensitive to the choice of using loan balance or the number of loans when calculating county-level HHI measures. As with every HHI measure, our variable moves in the opposite direction of competition. In other words, more competition leads to lower levels of *LocalSponsorHHI*. The HHI measure of competition aligns closely with our theoretical motivation where competition is captured by the probability of a competing sponsor arriving. In the limiting case, if a market is completely concentrated (i.e., $HHI \to 1$), we expect the probability of a competing sponsor arriving would be $\theta \to 0$. However, at high levels of competition ($HHI \to 0$), the probability that a competing sponsor arrives is almost certain, so $\theta \to 1$. Nevertheless, there are alternative ways to measure competition. As we discuss in Section 8, our results are robust to using concentration ratios that capture the market share of the top three sponsors within the county-year (Scharfstein and Sunderam, 2016).

4.2. The local nature of sponsor competition

We observe significant dispersion in our measure of local sponsor competition (Fig. 2), a fact we exploit in our empirical tests. But, if sponsors are large financial institutions with a national presence, why is competition local in nature? Our measure captures the spatial diversification constraint faced by sponsors while sourcing loans from originators. Sponsors and investors pay attention to the geographic distribution of collateral at the state level (see Internet Appendix Figure IA.B.2 for a sample MBS prospectus). Indeed, we find evidence that sponsor competition at the state level is positively correlated with the share of differentiated loans in the state (Internet Appendix Figure IA.B.3).

But in addition to state-level constraints, sponsors are also required to report the specific local area within a given state with

Table 1
Loan characteristics.

(a) Statistics by property type

	Standard loans		Differentiated loans		All loans	
	N	Avg. size	N	Avg. size	N	Avg. size
Single family	7,086,275	$199,788	5,517,863	$283,221	12,604,138	$236,313
PUD	926,719	$232,257	1,259,843	$284,065	2,186,562	$262,107
Other	1,751,375	$168,460	1,508,562	$222,910	3,259,937	$193,657

(b) Statistics by loan purpose

	Standard loans		Differentiated loans		All loans	
	N	Avg. size	N	Avg. size	N	Avg. size
Purchase	3,504,491	$191,961	3,862,903	$258,930	7,367,394	$227,074
Cash Out Refi	3,209,151	$194,675	2,348,908	$292,096	5,558,059	$235,846
Refinancing	1,686,349	$262,250	1,275,100	$349,602	2,961,449	$299,861
Other	1,364,378	$136,556	799,357	$156,151	2,163,735	$143,795

(c) Statistics by type of MBS

	Standard loans		Differentiated loans		All loans	
	N	Avg. size	N	Avg. size	N	Avg. size
Prime	1,551,076	$395,703	1,812,687	$439,067	3,363,763	$419,071
Subprime	5,725,372	$151,536	3,671,932	$182,481	9,397,304	$163,627
Alt-A	1,573,369	$201,826	2,076,092	$290,271	3,649,461	$252,140
Other	914,552	$138,990	725,557	$259,592	1,640,109	$192,342

This table describes loan characteristics of 18 million securitized loans over the period 1997–2008. Across all panels, summary statistics are shown separately for Standard and Differentiated loans, where a loan is defined as "Differentiated" if it takes any of the following features: Negative Amortization, Interest Only, Hybrid ARM, Option ARM, Balloon Payment or Pay Teaser. Standard loans are the complementary set of non-differentiated loans. N refers to the number of loans in each category and Avg. size refers to the mean of the original loan balance. In Panel (a), we provide summary statistics broken out by the property type. Note, *PUD* refers to "Planned Unit Development". Panel (b) provides summary statistics by loan purpose, as defined in ABSNet. Finally, in Panel (c) we provide summary statistics by the type of MBS, which refers to the MBS category of the securitized deal in ABSNet.

Table 2
County characteristics.

(a) All local markets

	Averages across counties					
	N	Mean	σ	p50	p25	p75
Number of loans (#)	7720	2341	8974	368	98	1388
Number of differentiated loans (#)	7720	1074	5336	56	9	397
Local Sponsor HHI	7696	0.178	0.153	0.129	0.081	0.208
Loan Demand	7711	2.11	0.32	2.09	1.88	2.32
Population (#)	7471	345,109	593,038	168,516	97,727	380,949
Total Personal Income ($ mn)	7471	$12.3	$22.7	$5.2	$2.8	$12.8
Employment (#)	7471	208,244	369,878	95,415	50,627	223,022

(b) Prime and non-Prime markets

	PrimeMarket			nonPrimeMarket		
	N	Mean	p50	N	Mean	p50
Number of loans (#)	4936	2744	381	2784	1627	350
Number of differentiated loans (#)	4936	1266	57	2784	732	54
Local Sponsor HHI	4923	0.177	0.129	2773	0.179	0.129
Loan Demand	4927	2.17	2.15	2784	2.02	1.99
Population (#)	4795	392,810	181,752	2676	259,636	155,842
Total Personal Income ($ mn)	4795	$13.5	$5.3	2676	$10.1	$5.2
Employment (#)	4795	242,552	105,672	2676	146,769	85,445

This table describes characteristics of local markets where sponsors compete for sourcing loans from originators. Summary statistics are presented at the county × year level over the period 1997–2008. Panel (a) summarizes data for all counties, whereas Panel (b) describes characteristics for the Treated (*PrimeMarket*) and Control (*SubprimeMarket*) counties. If the percentage of census tracts in a given county defined as *Underserved Areas* as per the HUD regulation are in the 25th percentile or below, then that county is classified as a *PrimeMarket*. This definition captures higher-income areas. Additional variable definitions can be found in Internet Appendix Table IA.B.2.

the highest concentration of the overall loan balance.[9] The cross-state diversification constraint, together with the within-state limit on local concentration, motivate our definition of sponsor competition at the *county-level*. Note that the nature of the diversification constraint on sponsors differs, depending on whether it is across states (more binding) or within a given state (less binding). As long as the sourcing of loans do not excessively concentrate in very local areas (i.e., ZIP codes), sponsors may have latitude in choosing loans within a given state. Indeed, our identification strategy in Section 6 using the HUD rule of 2000 exploits this within-state variation in sponsor competition. Note that in addition to these geographic constraints, local informational advantages through existing originator networks may be important to the deal's portfolio composition (Coval and Moskowitz, 2001).

Although we use sponsor HHI defined at the county level for most empirical tests, our main result is not sensitive to this definition. In the

[9] Bank of America's Asset Backed Funding Corporation Prospectus (dated October 3, 2006) for $1,386,432,000 reports: "The greatest ZIP Code geographic concentration of the initial group 1 Mortgage Loans by Principal Balance as of the Cut-off Date is expected to be approximately 0.63% in the 60629 ZIP Code, located in Illinois, for the initial group 2 Mortgage Loans is expected to be approximately 0.54% in the 92704 ZIP Code, located in California, and for all the Initial Mortgage Loans is expected to be 0.38% in the 33463 ZIP Code, located in Florida". [pg A-12].

alternate identification strategy (Section 8.2), we define sponsor HHI at the MSA level and continue to find consistent results.

4.3. Sample summary statistics

In Table 2 Panel (a), we present county-level summaries across our entire sample for the number of differentiated loans, average local sponsor competition, loan demand and other demographics. The detailed definitions of these variables are in Internet Appendix Table IA.B.2. The average value of our main independent variable (*LocalSponsorHHI*) is 0.178 with a standard deviation of 0.153. The typical county in our sample has an average population of 345,109 with a total personal income estimate of $12.3 mn. The number of employed persons on average is 208,244.

We study the differential competition response of sponsors across counties which are more or less exposed to the GSE regulatory shock. We term those areas more exposed to the shock as *nonPrimeMarkets*, and those less exposed as *PrimeMarkets*. In Table 2 Panel (b), we show differences in county characteristics between *PrimeMarkets* and *nonPrimeMarkets*. The county-year observations for *PrimeMarkets* are slightly higher than those of *nonPrimeMarkets*. Panel (b) shows that local sponsor competition levels are comparable across both markets. *PrimeMarkets* tend to have higher population, greater total personal income and employment levels relative to *nonPrimeMarkets*.

Internet Appendix Table IA.B.3 shows the distribution of loans based on the year of securitization. The table also shows the proportion of differentiated loans in each year. The table confirms the trend in Fig. 3 — the proportion of differentiated loans increased significantly in the early boom period. The average rate of differentiation in the overall sample is 46%, with significant heterogeneity (3.7% in 1999, 66.6% in 2007) across securitization years.

5. Sponsor competition and loan differentiation

We begin our empirical analysis by examining aggregate trends in sponsor competition and differentiation. In Fig. 3, as competition increases (Sponsor HHI decreases), we see a steady increase in the share of differentiated loans, with levels peaking just before the financial crisis (2007Q3). The share of loans with differentiated features is greatest when competition between the sponsors of securitizations is also the highest. In untabulated results, we find a similar pattern with differentiation intensity.

To better understand the relationship between sponsor competition and differentiated mortgages, our empirical strategy is comprised of a three-pronged approach. In this section, we provide results for the first two approaches before discussing our main identification strategy in Section 6.

5.1. Exploiting local variation in sponsor competition

In our baseline results in Table 3, we test whether the propensity of differentiation in securitized loans is greater in local markets that experience greater competition from sponsors. We regress an indicator for loan differentiation against local sponsor HHI. We use the cross-section of all securitized loans j in Eq. (17) where $X_{c,t}$ represents controls and/or fixed-effects at appropriate levels.[10] We cluster standard errors at the state-year level to account for (a) correlation in errors that may be driven by changes in the regulatory environment at the state-level affecting both competition and the rate of non-standard mortgages usage (such as anti-predatory lending laws), and (b) correlation due to other unobserved time-varying shocks that affect variation in competition and differentiation within the same state. We also show in Section 8 that our results are not sensitive to other reasonable choices in clustering. Running our analysis at the loan level, as opposed to the county level, is important so that we can account for sponsor details, observable loan characteristics, and other important within-county variation.

$$\mathbb{1}_{\text{Differentiation}_{j,c,t}} = \alpha + \boldsymbol{\beta}(\text{LocalSponsorHHI}_{c,t-1}) + X_{c,t-1} + \delta_{sponsor} + \delta_{state\times year} + \epsilon \tag{17}$$

Column (1) of Table 3 shows a robust negative relationship: a one standard deviation decrease in local sponsor HHI (i.e. increase in local competition) results in a 2.5 percentage point increase in the probability of observing a differentiated mortgage. In terms of the average differentiation of 46% (Internet Appendix Table IA.B.3), this translates into a relative increase of 5.4%. An immediate concern in interpreting this correlation is that securitization in the pre-crisis period was dominated by large institutions such as Countrywide, Bear Stearns, and Lehman Brothers, companies that were ultimately found lacking in their risk management practices (FCIC, 2011). So unobservable institutional characteristics (such as risk culture, in the sense of Fahlenbrach et al., 2012) may not only explain greater competition but also correlate with the increased differentiation. To address this question, all our regressions absorb institutional differences using sponsor fixed effects.

To ensure that our results in Table 3 are not confounded by the findings in Di Maggio et al. (2019), we control for State × Year fixed effects in all our regressions. These fixed effects have the advantage of controlling for average differences in the regulatory environment at the state level (such as APL laws). Even more, we allow for such differences to vary through time which can capture broad changes in economic conditions. Thus, it is unlikely that differences in the responses of originators to the OCC rule across states with and without APL laws can explain our results. As our later results will show, we document an effect many years prior to 2004, which cannot be explained by the effects of the OCC rule.

Since our regression uses variation in sponsor competition across local counties, Column (2) of Table 3 includes time-varying county-level observables such as population, employment and income that may be correlated with this variation.[11] These controls mitigate the possibility that our results are driven by demand factors specific to a geography because we compare local markets with comparable demographic factors. For instance, our results are unlikely to be driven by fundamental differences between urban and rural areas. Even more, Column (3) of Table 3 directly includes a measure of loan demand using data from HMDA mortgage applications. We find that greater sponsor competition is associated with more differentiated loans after controlling for loan demand. From Column (3) of Table 3, we see that borrower demand is negatively related to the propensity to issue differentiated contracts. The negative coefficient suggests that when borrower demand is high, originators utilize less differentiated mortgages. To the extent demand factors confound our interpretation, they bias against finding a result.

Nevertheless, observable controls may not fully account for time-varying *unobservable* demand factors within local markets that may confound our interpretation. In Column (4) of Table 3, we employ our most stringent specification which accounts for time-varying unobservables at a high level of granularity, with the inclusion of CBSA × Year fixed effects, in addition to demographic controls. We continue to find consistent results. In sum, we find strong, consistent evidence that an increase in local sponsor competition is associated with higher rate differentiation for securitized mortgages.

[10] We use a linear probability model to avoid the incidental parameters problem associated with fixed effects in logit regressions. However, using logit regressions (untabulated), we find our results are economically and statistically similar.

[11] We do not explicitly control for house prices because Dokko et al. (2019) show evidence that the rise in house prices were a *consequence* of the issuance of non-standard mortgage contracts, rather than a cause of it. See also Levitin and Wachter (2020) who make a similar argument.

Table 3
Higher sponsor competition associated with greater loan differentiation.

	Differentiation indicator			
	(1)	(2)	(3)	(4)
$LocalSponsorHHI_{c,t-1}$	−0.253*** (0.077)	−0.133** (0.054)	−0.133** (0.054)	−0.132*** (0.037)
$Population_{c,t-1}$		−0.131*** (0.017)	−0.106*** (0.017)	−0.062*** (0.010)
$Employment_{c,t-1}$		−0.035*** (0.009)	−0.034*** (0.009)	0.015** (0.006)
$Income_{c,t-1}$		0.167*** (0.014)	0.143*** (0.015)	0.042*** (0.007)
$LoanDemand_{c,t-1}$			−0.051*** (0.010)	−0.076*** (0.008)
Sponsor FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	–
CBSA × Year FE	–	–	–	Yes
Observations	18,020,433	17,462,253	17,462,253	17,434,827
R^2	0.205	0.208	0.208	0.212

This table reports the results of linear probability panel regressions investigating:

$$\mathbb{1}_{\text{Differentiation}_{j,c,t}} = \alpha + \beta_1(LocalSponsorHHI_{c,t-1}) + X_{c,t-1} + \delta_{sponsor} + \delta_{State\times Year} + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable is an indicator that captures the incidence of differentiation in a securitized loan. Differentiation for individual loans is calculated based on indicators for any of the following features: Hybrid ARM, Balloon, Interest Only, Negative Amortization, Pay Teaser, Option ARM. The main independent variable refers to lagged Sponsor HHI (Herfindahl–Hirschman Index) based on loan balances defined at the county-year level. Columns 2–4 include county-level, time-varying controls. Columns 3–4 include loan demand which is measured as the lagged ratio of HMDA applications to HMDA originations in a given county and year. The fixed effects included in each regression are denoted below the regression. Standard errors are clustered at the State × Year level. Detailed variable definitions can be found in Internet Appendix Table IA.B.2.

In our next set of tests, we utilize the variation in sponsor competition within the same originator and region for seemingly identical loans to help narrow the role of the sponsor competition in increased differentiation.

5.2. Variation in sponsor competition within originator

While the previous result helps addresses the challenge of correlated omitted variables arising from common shocks to sponsors or the regulatory environment in any given year, it may leave open the possibility that sponsor competition is correlated with the market dynamics of originators. Originators, not sponsors, make loans, so one could reasonably argue that variation in local sponsor HHI may be driven by the competition between originators. To address this identification concern, Table 4 performs a *within-originator* analysis. But data on originators in the ABSNet database is limited, so we assume loan servicers as a useful proxy. To support this assumption, we use the fact that in the pre-crisis period, a majority of originators also retained servicing rights for the mortgages they originated.[12] We ensure our results are not sensitive to this assumption by reporting consistent results with the original, limited sample of lenders in Internet Appendix Table IA.B.4.

The thought experiment is to take an originator that is in a relatively homogeneous lending market, at a given point in time, but is exposed to *different* levels of competition. If the originator's rate of differentiation varies across these sponsors, then it suggests that originator incentives to differentiate are engendered by sponsor competition. To this end, we estimate the effect of local sponsor HHI on differentiation by including

[12] In Ashcraft et al. (2008), top 10 originators such as HSBC, Countrywide, Citigroup, Ameriquest, Option One, Wells Fargo were also listed under the top 10 mortgage servicers (See Tables 2 and 4).

Table 4
Greater sponsor competition within the same originator leads to higher loan differentiation.

	Differentiation indicator			
	(1)	(2)	(3)	(4)
$LocalSponsorHHI_{c,t-1}$	−0.226*** (0.065)	−0.120*** (0.044)	−0.121*** (0.044)	−0.096*** (0.027)
$Population_{c,t-1}$		−0.109*** (0.013)	−0.090*** (0.013)	−0.050*** (0.007)
$Employment_{c,t-1}$		−0.029*** (0.007)	−0.029*** (0.007)	0.011** (0.004)
$Income_{c,t-1}$		0.138*** (0.011)	0.121*** (0.012)	0.036*** (0.006)
$LoanDemand_{c,t-1}$			−0.038*** (0.007)	−0.061*** (0.007)
Sponsor FE	Yes	Yes	Yes	Yes
Originator × State × Year FE	Yes	Yes	Yes	–
Originator × CBSA × Year FE	–	–	–	Yes
Observations	17,782,788	17,234,366	17,234,366	17,137,086
R^2	0.358	0.360	0.360	0.371

This table reports the results of linear probability panel regressions investigating:

$$\mathbb{1}_{\text{Differentiation}_{j,c,t}} = \alpha + \beta_1(LocalSponsorHHI_{c,t-1}) + X_{c,t-1} + \delta_{sponsor} + \delta_{Originator\times State\times Year} + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable is an indicator that captures the incidence of differentiation in a securitized loan. Differentiation for individual loans is calculated based on indicators for any of the following features: Hybrid ARM, Balloon, Interest Only, Negative Amortization, Pay Teaser, Option ARM. Importantly, the empirical strategy includes Originator × State × Year fixed effects, so the identifying variation compares the same originator in the same state at the same point in time, but exposed to differing levels of sponsor competition. The main independent variable refers to lagged Sponsor HHI (Herfindahl–Hirschman Index) based on loan balances defined at the county-year level. Columns 2–4 include county-level, time-varying controls. Columns 3–4 include loan demand which is measured as the lagged ratio of HMDA applications to HMDA originations in a given county and year. The fixed effects included in each regression are denoted below the regression. Standard errors are clustered at the State × Year level. All variables are defined in Internet Appendix Table IA.B.2.

Originator × State × Year fixed effects. By analyzing loan differentiation within the same originator in the same geographic region (state) and year, our research design helps isolate the effect of sponsors because variation in differentiation can no longer be purely attributed to time-varying differences at the originator level. As discussed earlier, these tight fixed effects subsume effects of APL law differences that motivate the analysis in Di Maggio et al. (2019). In column (1) of Table 4, we find a one standard deviation increase in sponsor competition (decrease in HHI) results in a 2.4 percentage point increase in the probability of differentiation, translating to an 5.2% increase in economic terms.

As in Table 3, we control for time-varying unobservable local characteristics as well as demand conditions that may confound our interpretation. Thus, we are effectively comparing loans in observably identical local geographies, made by the same originator at a similar point in time and location, but one loan is made in an area that is exposed to significantly more sponsor competition than the other area. Such a tight comparison rules out the possibility that local sponsor HHI may proxy for unobservable local characteristics that are also correlated with differentiated features. In sum, the results of Table 4 reinforce the earlier finding that sponsor competition likely contributed to the increased differentiation of securitized mortgages.

6. Exogenous variation in sponsor competition

Despite the within-originator analysis and the use of high-dimensional fixed effects, one might still worry that variation in local sponsor HHI may be correlated with omitted factors unobservable to the econometrician. To confound our interpretation, however, these unobservable factors must not only explain variation in local sponsor competition and loan differentiation, but also be unrelated to key

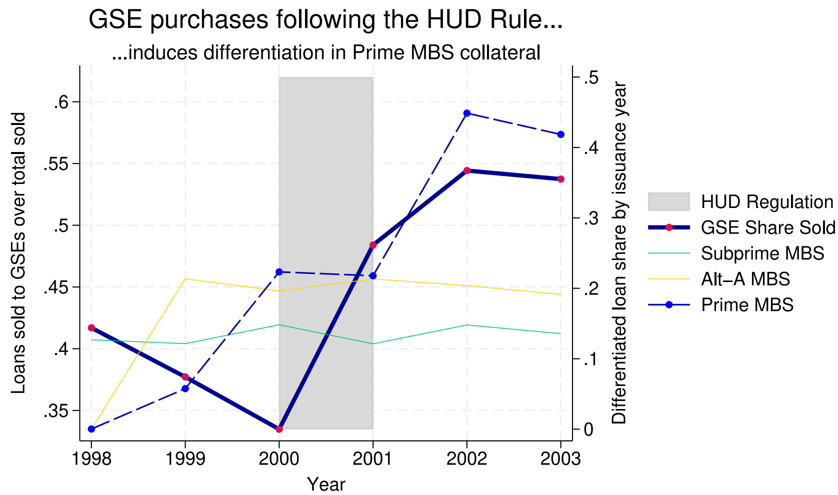


Fig. 5. Response of GSEs to the affordable housing act. This figure tracks the time-series evolution of GSE market share and differentiated mortgage prevalence in the non-prime and prime markets over the period of 1998–2003. GSE market share is defined as the number of HMDA loans sold to GSEs over all loans sold and is displayed with the bold blue line (values correspond to the y-axis on the left). Conditional on a HMDA loan being sold, a greater share was purchased by GSEs following the announcement of the HUD rule in 2000. The blue dashed line captures the prevalence of differentiated loans in Prime MBS deals (values correspond to the y-axis on the right). Notably, the figure shows that GSE purchases following the HUD rule coincides with the rise in differentiation of Prime MBS collateral. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

loan characteristics or originator and time-specific effects. While we believe such a possibility is less likely, we cannot rule it out unless we can find plausibly exogenous variation in local sponsor competition. To overcome the identification hurdle, we set up a difference-in-differences research design around a regulatory change that identifies an exogenous source of variation for sponsor competition.

6.1. The HUD rule of 2000

In 1992, Congress passed the Affordable Housing Act giving the U.S. Department of Housing and Urban Development (HUD) the right to set affordable housing purchase goals for Fannie Mae and Freddie Mac, the government sponsored enterprises (GSEs). In 1996, these GSEs were expected to source 40% of all eligible loans from low to moderate income households. That limit was changed to 42% for 1997 to 1999. Then, the biggest change (which is the focus of our research design) came in 2000 when the limit was revised to 50% for the years 2001–2003. This represents a one-year increase of almost 20% in the allocation of GSE loans to lower-income areas. The goals remained in effect for 2004 and beyond.

We exploit the HUD rule of 2000 (which significantly raised the limit of GSE purchases) to generate plausibly exogenous variation in local sponsor HHI. Fig. 5 shows a large jump in the loans sold to the GSEs following the 2000 regulatory change. Prior to the rule change, 45%–50% of all loans originated were sold to the GSEs. However, after the rule went into effect in 2001, the share of loans sold to the GSEs abruptly increased to approximately 60% of all originated loans.

Not only did the rule change increase the market share of the GSEs, the Affordable Housing Act also required the GSEs to focus on less creditworthy borrowers. A loan counted towards the GSEs' affordable housing goal if the corresponding census tract had a median family income less than or equal to 90% of the median family income in the respective MSA or a minority share of at least 30%. Bhutta (2012) finds that the HUD rule had a causal effect of increasing GSE purchases in underserved areas. The impact on competition among *private securitizers*, however, remains an empirical question. On the one hand, if private securitizers are competing in a restricted market of low-income borrowers, it is possible that the HUD rule increased competition in lower-income counties. On the other hand, if GSE purchases crowd out loans to more creditworthy borrowers, we may expect greater incentives for private securitizers to compete more intensely in areas *less* affected by the HUD rule. In the next subsection, we differentiate between these possibilities and investigate the HUD rule's effect on sponsor competition and loan differentiation.

6.2. Effect of the 2000 HUD rule on private securitizer competition and loan differentiation

We estimate a dynamic difference-in-differences regression at the county-year level to test the effects of the HUD rule on local sponsor competition and loan differentiation (y):

$$y = \alpha + \sum_{t=1}^{T} \beta_t (PrimeMarket_c \times \delta_t) + PrimeMarket_c + \sum_{t=1}^{T} \delta_t + \delta_c + \epsilon \quad (18)$$

We follow Bhutta (2012) and the HUD's definition of Underserved Areas (UA) based on the 1993 census as those census tracts whose median income is less than 90% of the MSA median income. Since our analysis is at the county level, we calculate the percentage of census tracts classified as UA in any given county. Since we want to test for effects of private securitizer competition in areas less affected by the rule change, we define *PrimeMarket* counties as those whose percentage of census tracts qualifying as UA are in the 25th percentile or below. Based on this definition, those counties not classified as prime markets serve as the control group.[13] Internet Appendix Table IA.B.6 presents a comparison of treated and control counties prior to the law change.

Results in Gabriel and Rosenthal (2010) suggest the 2000 HUD Rule may have crowded out competition in areas where GSEs increased their purchases most. The intuition for our tests is predicated on private label activity being crowded out to areas that were least likely to see increases in GSE activity. Put differently, we suspect that private label securitizers will compete against one another more in areas where the HUD rule is unlikely to have a binding effect. In Internet Appendix Table IA.B.7, we show that the rule had a meaningful impact on the share of loans purchased by GSEs. In the years immediately following the rule change, we find that GSEs bought a greater share of mortgages in the counties most affected by the HUD requirement. An analogous

[13] In Internet Appendix Table IA.B.5 we obtain consistent results when we define *PrimeMarket* as counties whose percentage of census tracts classified as UA are in 50th percentile or below. Thus, our results are not sensitive to the specific definition of *PrimeMarket*.

interpretation is that GSEs were now purchasing a relatively lower share of loans in the *PrimeMarket* counties.

Next, we test the intuition that the GSEs' decreased prevalence in *PrimeMarket* counties resulted in increased sponsor competition by examining a county-year difference-in-differences regression where the outcome variable is local sponsor competition. We control for county and state-year fixed effects to account for any time-invariant differences across county and the general increase in state-level competition through time, respectively.[14] In Table 5, we confirm that the timing of the rule coincides with a statistically significant increase in sponsor competition in the *PrimeMarket* counties. We find the effect peaks in economic significance in 2000, then slowly dissipates in economic and statistical significance through the end of our sample. The coefficient of −0.022 in 2000 suggests a 12.3% relative increase in competition, relative to the mean. These results lay the foundation for our interpretation that any changes in differentiated mortgages flows through the rule's effect on local sponsor competition.

Note that if the entry of GSEs increased *overall* competitive pressure in the low-income (control) counties for the types of loans that PLS sponsors were targeting, we might worry that the effect of the HUD rule on sponsor competition is ambiguous. In this alternate explanation, GSEs compete with private sponsors in the low-income areas (i.e. overall competition, PLS + GSE, increased), rather than crowding private sponsors out into the high-income regions. To distinguish the GSE competition hypothesis from the crowding out story (laid out in Internet Appendix Table IA.B.8), we expand our data to include GSE-securitized loans and examine whether overall (PLS + GSE) competition increases in the control regions. Internet Appendix Table IA.B.9 rejects this explanation, in favor of the crowding-out effect.

Next, we test whether the increased competition that resulted from the rule change impacted mortgage differentiation. Given our previous analysis, we expect differentiation to increase more in prime markets in the presence of a crowding-out effect. The base year (1999) is omitted in the estimation. Table 6 presents the results.

The coefficients of interest are the interaction terms β_t. Table 6 shows an increase in loan differentiation in the years following the HUD rule for *PrimeMarket* counties. Between the years 2001 and 2004, differentiation increased more in prime markets relative to non-prime counties due to the increase in private sponsor competition in those markets. Note that county fixed effects control for (time invariant) county characteristics that may confound our results. State-year fixed effects will account for any legal or broad time-varying economic unobservables. Consistent with the timing of increases in competition, we find that differentiation significantly increases starting in 2001 by 2.3 to 3 percentage points. In terms of average differentiation in 2001, this effect translates into an economic magnitude of 15%–20%. The economic significance of this effect increases in subsequent years, peaking in 2004.

In support of parallel trends, the coefficients are statistically insignificant prior to the rule change, a necessary condition for a causal interpretation. Mortgage differentiation in Prime and non-Prime markets was not different prior to the regulatory change, but suddenly diverged after its implementation. These results help explain the divergence in the rise of differentiated collateral of prime and non-prime MBS in the early 2000s, seen in Fig. 5. Overall, Table 6 shows evidence of differentiation increasing in *PrimeMarket* counties after the law change, consistent with sponsor-induced competition resulting in greater differentiation at the loan level.

Bhutta (2012) argues that effects of the HUD rule may have diverged from the rule's original intent because there is limited evidence of an overall increase in mortgage credit supply due to the HUD rule. Not only did the rule potentially not achieve its primary goal of increasing aggregate mortgage credit supply, but it may also have had an unintended consequence — we document an increase in competition among private securitizers in higher-income counties which ultimately led to greater use of non-standard mortgages in securitized loan contracts. The fact that the rule increased competition, and ultimately differentiation, in areas that were of higher borrower quality provides a potential explanation why differentiated mortgages grew first in prime MBS collateral in the early 2000s, prior to non-prime MBS collateral. This result is consistent with the second empirical prediction of our model in Section 3. Higher-credit-quality loans have a lower threshold of competition to warrant increased differentiation. Taken together, our result reconciles a seemingly puzzling fact about prime borrowers' use of non-standard mortgages by pointing to the role of sponsor competition in affecting the timing and places where differentiation occurred.

Table 5
Change in sponsor competition in prime markets after the HUD rule.

	Double difference estimates Local Sponsor HHI		
	(1)	(2)	(3)
PrimeMarket × 1997	−0.011	−0.011	−0.014
	(0.009)	(0.009)	(0.010)
PrimeMarket × 1998	−0.003	−0.003	−0.006
	(0.006)	(0.006)	(0.005)
PrimeMarket × 2000	−0.022***	−0.022***	−0.026***
	(0.006)	(0.006)	(0.006)
PrimeMarket × 2001	−0.018***	−0.018***	−0.019***
	(0.006)	(0.006)	(0.006)
PrimeMarket × 2002	−0.013***	−0.013***	−0.015***
	(0.005)	(0.005)	(0.005)
PrimeMarket × 2003	−0.007	−0.007	−0.011**
	(0.005)	(0.005)	(0.005)
PrimeMarket × 2004	−0.008*	−0.008*	−0.012***
	(0.005)	(0.004)	(0.005)
PrimeMarket × 2005	−0.006	−0.006	−0.010*
	(0.005)	(0.005)	(0.005)
PrimeMarket × 2006	−0.007	−0.007	−0.010**
	(0.005)	(0.005)	(0.005)
PrimeMarket × 2007	−0.006	−0.006	−0.012**
	(0.005)	(0.005)	(0.005)
PrimeMarket × 2008	−0.004	−0.004	−0.008
	(0.010)	(0.010)	(0.010)
Control for loan demand?	No	Yes	Yes
Control for time-varying County Char.?	No	No	Yes
County FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Observations	7655	7646	7192
R^2	0.823	0.823	0.741

This table reports the results of dynamic differences-in-differences panel regressions investigating:

$$HHI_{c,t} = \alpha + \sum_{t=1}^{T} \beta_t (PrimeMarket_c \times \delta_t) + PrimeMarket_c + X_{c,t-1} + \sum_{t=1}^{T} \delta_t + \delta_c + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable is local Sponsor HHI (Herfindahl–Hirschman Index) based on loan balances defined at the county-year level. In our dynamic difference-in-differences research design, *PrimeMarket* is an indicator variable that takes the value of one if the percent of census tracts designated as an underserved areas falls below the 25th percentile and zero otherwise. Column (2) includes county loan demand and column (3) includes time-varying county-level characteristics. Additional variable definition details can be found in Internet Appendix Table IA.B.2. All regressions include County and State × Year fixed effects, which subsume the Prime Market indicator and annual dummy indicators. Standard errors are clustered at the State × Year level.

7. High competition and marginal borrowers

The analysis thus far suggests that sponsor competition led to an increase in mortgage-level product differentiation, consistent with our model's first theoretical prediction. These features were focused on

[14] Of the CBSAs and counties included in our final sample, more than two-thirds of CBSAs have only treated or control counties present. This limits our ability to utilize CBSA × Year fixed effects in this set of empirical results.

the prime segment in the early boom period, as shown by results in Section 6. As non-standard features become more common, we expect sponsors to increasingly seek alternative ways to differentiate themselves even more. This product differentiation may have appealed to marginal borrowers, who could not have obtained a standard mortgage. As described in Proposition 4 of our theory model (Section 3) and Fig. 4 Panel (b), we can consider a second threshold for competition (θ^{**}). At very high levels of competition, we expect sponsor-induced product differentiation to target the non-prime segment.[15]

To test this hypothesis, we first plot the time-series evolution of non-standard mortgages across prime and marginal borrowers (Fig. 6 Panel (a)). Separating borrowers by credit quality aligns with the model's classifications of "access" (those with regular access to credit) and "marginal" (those without credit access). Product differentiation is associated with marginal borrowers in the later part of our sample. To investigate this pattern further, we test whether there is a structural break in the level of competition and the allocation of non-standard mortgages across different borrower characteristics. Panel (b) of Fig. 6 shows that at very high levels of competition (HHI < 0.1), the allocation of differentiated mortgages begins to dramatically tilt towards lower credit quality borrowers. These figures are consistent with the predictions from our theory model (Section 3.2).

To formally test the effect of different regimes of competition, we create two spline variables $\text{SponsorHHI}^{high} \in (0.1, 1)$ and $\text{SponsorHHI}^{low} \in (0, 0.1)$ at the knot point $\text{SponsorHHI} = 0.1$. Note that the spline variables are continuous measures (not indicators). We interact these measures with an indicator variable for whether the borrower is marginal or not. We then use our originator fixed effect model to test whether higher levels competition have a differential impact for marginal borrowers. In Table 7, we test whether the sponsor-induced product differentiation has greater sensitivity at higher levels of competition (SponsorHHI^{low}) for the marginal borrowers. A negative coefficient is obtained for $\text{SponsorHHI}^{low} \times$MarginalBorrower (i.e. increasing competition for marginal borrowers) but not for $\text{SponsorHHI}^{high} \times$ Marginal Borrower. This difference suggests that sponsor-induced product differentiation is greatest for marginal borrowers, but only at the highest levels of competition. We interpret this evidence as consistent with our model's second prediction (Section 3.2). In Table 8 we test whether the intensity/degree of product differentiation (measured by the number of non-standard features) is higher for marginal borrowers at high levels of competition, and find consistent results as well.

Finally, using HMDA data on mortgage applications we test whether the denial rates on these applications is different for marginal borrowers in high competition areas. The analysis in Table 9 is at the county level. A lower denial rate is suggestive of borrower pool expansion. The interaction term $\text{SponsorHHI}^{low} \times$MarginalBorrower is positive and statistically significant. Since lower HHI signals higher competition, this result shows that at very high levels of competition (i.e. decreasing HHI), denial rates are lowest for marginal borrowers. Although we find a similar result for lower levels of competition in some specifications, the economic magnitude is considerably higher at the highest levels of competition. This evidence is consistent with the notion that, in highly competitive areas, sponsors offered non-standard contract terms as a means to expand the borrower pool to those with lower credit quality.

Overall, the evidence in this section provides support for the notion that product differentiation by sponsors also led to market expansion targeting marginal borrowers.[16] Pairing the marginal borrower analysis with our earlier results demonstrates that product differentiation served two purposes. First, there is a fundamental motivation for sponsors to offer differentiated products to investors when facing greater competition. Second, at very high levels of competition, sponsors utilize differentiated mortgages as a way to expand the borrower pool to marginal borrowers who may not have qualified, or desired, standard mortgages. These results provide empirical support for the model's predictions and help provide a supply-side explanation for the timing and rise of differentiated mortgages across prime and non-prime borrowers.

8. Robustness checks

Our results strongly suggest that sponsor competition was an important contributor to the run-up in mortgage differentiation prior to the Global Financial Crisis. To ensure our conclusions are not sensitive to the empirical and modeling choices made in the analyses, we run a battery of robustness checks around these choices/assumptions.

8.1. Addressing concerns of measurement error

To verify that our baseline results are not driven by the specific definition of competition, we replicate our results from Table 3 using a measure of competition based on loan counts instead of loan balances (Internet Appendix Table IA.B.10). We find consistent results. We replace the Herfindahl index using an alternative measure of competition following Scharfstein and Sunderam (2016). Internet Appendix Tables IA.B.11 and IA.B.12 finds consistent results using the concentration of loans sold to the top three sponsors in a given county-year. This evidence suggests that our results are not driven by the specific formulation of the Herfindahl index.

In Internet Appendix Table IA.B.4, we use the original, limited sample of originators classified by the ABSNet database to show that our findings are not sensitive to the choice of originator definition in Table 4. Internet Appendix Table IA.B.4 also shows that our results are robust to alternate fixed effect structures that restrict comparisons to observably identical loans.

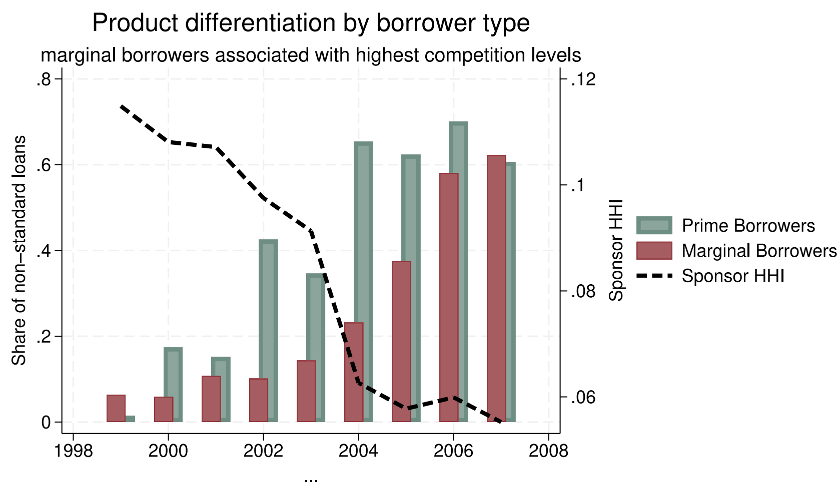
For our DiD specifications, we show evidence that the choice in how we define $Treated$ and $Control$ counties based on census tract proportions does not alter our interpretation. Internet Appendix Table IA.B.5 continues to find consistent results that counties with below-median proportion of underserved areas experience greater mortgage-level differentiation relative to the control group, after the passage of HUD regulation. Using the DiD framework, we also show that our choice of clustering standard errors does not affect the statistical significance of our main DiD tests (Internet Appendix Table IA.B.13). Finally, in Internet Appendix C.1 we discuss concerns of the stable unit treatment value assumption (SUTVA) that potentially arises from GSE entry causing sponsors to exit particular locations. We use both location-based and sponsor-based approaches to mitigate these concerns. In Internet Appendix Tables IA.C.1–IA.C.4 we motivate the analyses and find results that are nearly identical to our main DiD coefficients, mitigating SUTVA concerns that could bias our results or interpretation. We explain these tests in detail in Internet Appendix C.1.

Our definition of sponsor competition uses a county-level aggregation of the HHI measure (discussed in Section 4.2). Such aggregation also allows us to account for variation in state-level regulatory changes in the lending market via state-year fixed effects. Nevertheless, our results are not sensitive to the unit of aggregation since we find consistent estimates with sponsor competition defined at the state-level (Internet Appendix Figure IA.B.3) and MSA level (Internet Appendix C.2). Finally, Internet Appendix Table IA.B.14 shows that the main result obtains, even without the inclusion of $State \times Year$ fixed effects.

[15] We thank an anonymous referee for this suggestion.

[16] As private label sponsor competition resulted in an expansion into the marginal borrower segment, via differentiated loans, this change potentially explains the decline in FHA loan originations from about 20% to 4% over the period 2000–2007 (Demyanyk and Kolliner, 2015).

(a) Time series evolution of differentiated loans in prime and marginal borrowers



(b) Product differentiation targets marginal borrowers at high levels of competition

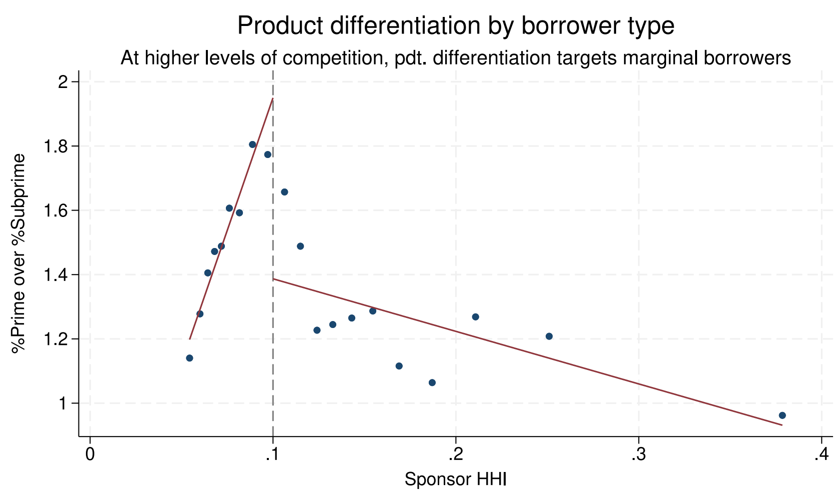


Fig. 6. Product differentiation, marginal borrowers, sponsor competition. This figure plots product differentiation by borrower type in the time series (Panel a) and in the cross-section of varying levels of SponsorHHI (Panel b). Panel (a) shows that the share of differentiated loans increases for marginal borrowers in the years just before the crisis. In the early boom period, the growth in differentiated products is observed in prime borrowers. Panel (b) shows the ratio of differentiated loans in the prime segment (as a percentage of total loans) over similar loans in the subprime segment. As we move from the right to the left on the x-axis, competition increases (SponsorHHI decreases). At lower levels of competition, there is more product differentiation in prime relative to subprime. But this pattern reverses at high levels of competition. This regime change happens around SponsorHHI = 0.1.

8.2. Alternative identification strategy

In Internet Appendix C.2, we provide an alternative identification strategy that utilizes an instrument for sponsor competition at the MSA level. Hurst et al. (2016) show that private sponsors react to changes in local default risk of mortgages, with sponsors sourcing more loans from areas that reduce their local default risk. Sponsors' tendency to tilt their loan sourcing to areas with lower default risk is then likely to affect local sponsor competition. Thus, our alternative identification strategy utilizes local default risk as an instrumental variable for sponsor competition. Internet Appendix Figure IA.C.1 shows a strong first stage relationship. The measure of default risk is provided at the MSA-quarter level rather than the county-level, making a direct comparison of magnitudes with our baseline tests difficult. Nevertheless, and despite the different geographic level of sponsor competition, we find that sponsor competition led to loan-level differentiation (Internet Appendix Table IA.C.5). This helps provide yet another piece of evidence for our main mechanism, and one that is neither predicated on the choice of county-level aggregation nor on the effects of the HUD regulation. We provide the result and a discussion of the exclusion restriction in Internet Appendix C.2.

Overall, the battery of tests presented in this section strengthens our main interpretation of the role of sponsor competition in explaining differentiation in mortgage contracts.

9. Delinquencies of differentiated loan contracts

In this section, we compare the delinquency performance of MBS collateral across prime and non-prime (Subprime, Alt-A) categories. We track delinquency statuses of securitized loans over a long time horizon (from the year of its securitization until a decade after the onset of the crisis (i.e., 2017)). We use an indicator that takes a value of one if the loan is in any of the following statuses: 60+ days delinquent, 90+ days delinquent, bankrupt, foreclosed, REO or liquidated with loss.[17] Ceteris paribus, we expect delinquency rates for the collateral of (low-yield) prime MBS to be lower than that of (higher-yield) non-prime MBS.

Table 10 presents delinquency statistics for standard and differentiated loans across prime and non-prime categories. In the early boom period (2000–2004), we find that over $90 billion of differentiated Prime MBS collateral ended up becoming delinquent. This is higher than the sub-total for standard loans ($68.5 bn). This period coincides with the increase in sponsor-induced product differentiation following the HUD regulation. The delinquency estimate is higher even relative to differentiated collateral of the Subprime and Alt-A MBS ($24.5 bn and $16.3 bn respectively), suggestive of higher growth in product differentiation for that segment. During 2005–2008, this pattern gets reversed. Delinquencies for non-prime categories significantly increase, coinciding with our result in Section 7 that competition-induced product differentiation targets the marginal borrower segment.

These results offer support for two non-competing interpretations. First, the fact that delinquencies are larger in the prime segment in the early boom period, suggests that sponsor-induced product differentiation was a means to obfuscate the quality of products offered to investors. Ghent et al. (2017) show that MBS deals with greater deal complexity defaulted at a greater frequency than standard MBS, and investors did not perceive differentiated products offered by sponsors as being riskier, ex-ante. Thus, our loan-level evidence is consistent with their findings. Second, the fact that differentiated mortgages in the marginal borrower segment performed relatively worse later in the sample suggests that sponsor-induced credit expansion may have led to a build up of risk just before the crisis.

10. Conclusion

The use of non-standard mortgage features increased dramatically in the pre-crisis period. These mortgages defaulted at significantly higher rates in times of market distress, deepening the financial crisis. Using a database of over 18 million securitized loans, we provide plausible causal evidence that increased competition among MBS sponsors played a key role in driving the increase in non-standard features in home mortgages. Sponsor-induced competition not only explains the role of securitization markets in loan-level differentiation, but also sheds light on why differentiation in Prime MBS preceded that of non-Prime MBS in the early boom period. Our results strongly suggest that securitization sponsors are not merely passive conduits of differentiated mortgages, but rather contributors to the significant increase in non-standard mortgages during the pre-crisis period. We have shown that the government-mandated purchases of loans from underserved areas can have unintended consequences, raising potential additional costs regarding the effectiveness of affordable housing regulation. Our evidence of MBS sponsors influencing the design of the underlying assets on which the derivatives are written presents an interesting challenge for theoretical models on security design.

Following the financial crisis, private label securitizers exited the RMBS market, leaving the current market to be predominantly run by the GSEs. Yet, the *origination* market remains highly competitive with the increasing entry of non-bank mortgage companies (Buchak et al., 2018), who rely almost exclusively on selling loans to the GSEs. As a result of GSE dominance and post-crisis regulation, mortgages are increasingly "standardized".[18] In light of our findings, this trend of increasing non-bank competition along with institutional constraints that standardize product features predicts a shift towards *process*-based differentiation in today's mortgage market. The proliferation of technology-based lenders (i.e. FinTech) is consistent with these players differentiating on the cost/process dimension — via new, automated loan processing and underwriting methods. Indeed, recent research provides robust empirical evidence that FinTech originators have faster loan processing times (Fuster et al., 2019). Thus, our evidence on the link between competition and product differentiation points to a mechanism that is generalizable to today's mortgage markets.

Table 6
Differentiation induced in prime markets by the HUD rule of 2000.

	Double difference estimates Loan differentiation		
	(1)	(2)	(3)
PrimeMarket × 1997	0.002	0.002	0.005
	(0.011)	(0.011)	(0.013)
PrimeMarket × 1998	−0.004	−0.004	−0.002
	(0.009)	(0.009)	(0.012)
PrimeMarket × 2000	0.014	0.014	0.010
	(0.010)	(0.010)	(0.011)
PrimeMarket × 2001	0.030**	0.029**	0.023**
	(0.012)	(0.012)	(0.011)
PrimeMarket × 2002	0.043***	0.044***	0.032***
	(0.014)	(0.014)	(0.012)
PrimeMarket × 2003	0.035***	0.036***	0.021**
	(0.008)	(0.008)	(0.010)
PrimeMarket × 2004	0.047***	0.048***	0.030***
	(0.007)	(0.007)	(0.009)
PrimeMarket × 2005	0.041***	0.042***	0.021**
	(0.007)	(0.007)	(0.009)
PrimeMarket × 2006	0.032***	0.033***	0.009
	(0.008)	(0.007)	(0.010)
PrimeMarket × 2007	0.022***	0.023***	−0.001
	(0.008)	(0.008)	(0.011)
PrimeMarket × 2008	0.001	0.004	−0.021
	(0.013)	(0.013)	(0.014)
Control for loan demand?	No	Yes	Yes
Control for time-varying County Char.?	No	No	Yes
Sponsor FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Observations	18,022,263	17,721,204	17,462,253
R^2	0.212	0.212	0.211

This table reports the results of dynamic differences-in-differences panel regressions investigating:

$$\mathbb{1}_{\text{Differentiation}_{j,c,t}} = \alpha + \sum_{t=1}^{T} \beta_t (PrimeMarket_c \times \delta_t) + PrimeMarket_c + X_{c,t-1} + \sum_{t=1}^{T} \delta_t + \delta_c + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable is a loan-level indicator variable that takes the value of one if the loan contains any of the following features: Hybrid ARM, Balloon, Interest Only, Pay Teaser, Negative Amortization, Option ARM. In our dynamic difference-in-differences research design, *PrimeMarket* is an indicator variable that takes the value of one if the percent of census tracts designated as an underserved areas falls below the 25th percentile and zero otherwise. Column (2) includes county loan demand. Column (3) includes the following time-varying county-level characteristics: Population, Employment, and Personal Income at the county level. Additional variable definition details can be found in Internet Appendix Table IA.B.2. All regressions include County and State × Year fixed effects, which subsume the Prime Market indicator and annual dummy indicators. Standard errors are clustered at the State × Year level.

[17] Internet Appendix Table IA.B.2 provides a complete definition. For loans classified as "Other" in the ABSNet database, we trace their 12 month history and re-classify them based on whether they were delinquent or current/paid-in-full based on that history.

[18] The main reasons for this trend include (a) adherence to GSE conforming standards to be eligible for securitization, and (b) greater originations of loans satisfying the Qualified Mortgage (QM) rule introduced in 2014 by the Consumer Finance Protection Bureau (which disallowed non-standard features such as interest-only and balloon payments).

Table 7
Competition, product differentiation and marginal borrowers.

Spline regression	Product Differentiation Indicator			
	(1)	(2)	(3)	(4)
$\text{SponsorHHI}^{low} \times$ Marginal Borrower	−5.949***	−5.870***	−5.866***	−6.112***
	(0.743)	(0.733)	(0.735)	(0.457)
$\text{SponsorHHI}^{high} \times$ Marginal Borrower	1.108***	1.176***	1.168***	1.333***
	(0.241)	(0.214)	(0.217)	(0.165)
SponsorHHI^{low}	3.800***	4.117***	4.064***	4.282***
	(0.795)	(0.683)	(0.681)	(0.428)
SponsorHHI^{high}	−1.082***	−1.045***	−1.033***	−1.128***
	(0.254)	(0.210)	(0.213)	(0.159)
Marginal Borrower	0.288***	0.288***	0.288***	0.311***
	(0.062)	(0.061)	(0.061)	(0.038)
Controls	No	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes
Originator × State × Year FE	Yes	Yes	Yes	–
Originator × CBSA × Year FE	–	–	–	Yes
Observations	16,319,290	15,817,053	15,817,053	15,727,555
R^2	0.363	0.364	0.364	0.374

This table reports the results of a spline regression investigating:

$$\mathbb{1}_{\text{Differentiation}_{j,c,t}} = \alpha + \boldsymbol{\beta_1}(\text{SponsorHHI}^{low}_{c,t-1} \times \text{MarginalB.}) + \boldsymbol{\beta_2}(\text{SponsorHHI}^{high}_{c,t-1} \times \text{MarginalB.}) + \boldsymbol{\beta_3}(\text{SponsorHHI}^{low}_{c,t-1}) + \boldsymbol{\beta_4}(\text{SponsorHHI}^{high}_{c,t-1}) + X_{c,t-1} + \delta_{sponsor} + \delta_{Orig.\times St.\times Yr} + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable is an indicator that captures the incidence of product differentiation in a securitized loan. Differentiation for individual loans is calculated based on indicators for any of the following features: Hybrid ARM, Balloon, Interest Only, Negative Amortization, Pay Teaser, Option ARM. Importantly, the empirical strategy includes Originator × State × Year fixed effects, so the identifying variation compares the same originator in the same state at the same point in time, but exposed to differing levels of sponsor competition. The two main variables $\text{SponsorHHI}^{low}_{c,t-1}$ and $\text{SponsorHHI}^{high}_{c,t-1}$ are splines of SponsorHHI, defined using the cutoff point SponsorHHI = 0.1 motivated by Panel (b) of Fig. 6. MarginalBorrower is an indicator for borrowers classified as Subprime and Alt-A. Columns 2–4 include county-level, time-varying controls. Columns 3–4 include loan demand which is measured as the lagged ratio of HMDA applications to HMDA originations in a given county and year. The fixed effects included in each regression are denoted below the regression. Standard errors are clustered at the State × Year level. All variables are defined in Internet Appendix Table IA.B.2.

Table 8
Competition, product differentiation intensity and marginal borrowers.

Spline regression	Degree of Product Differentiation			
	(1)	(2)	(3)	(4)
$\text{SponsorHHI}^{low} \times$ Marginal Borrower	−5.902***	−5.835***	−5.827***	−6.330***
	(1.836)	(1.800)	(1.805)	(1.059)
$\text{SponsorHHI}^{high} \times$ Marginal Borrower	2.377***	2.545***	2.529***	2.828***
	(0.453)	(0.410)	(0.415)	(0.317)
SponsorHHI^{low}	2.956	3.681**	3.568**	4.534***
	(1.848)	(1.623)	(1.621)	(0.829)
SponsorHHI^{high}	−2.196***	−2.131***	−2.106***	−2.257***
	(0.459)	(0.385)	(0.390)	(0.309)
Marginal Borrower	0.043	0.050	0.050	0.097
	(0.165)	(0.163)	(0.164)	(0.095)
Controls	No	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes
Originator × State × Year FE	Yes	Yes	Yes	–
Originator × CBSA × Year FE	–	–	–	Yes
Observations	16,319,290	15,817,053	15,817,053	15,727,555
R^2	0.459	0.460	0.460	0.469

This table reports the results of a spline regression investigating:

$$y_{i,c,t} = \alpha + \boldsymbol{\beta_1}(\text{SponsorHHI}^{low}_{c,t-1} \times \text{MarginalB.}) + \boldsymbol{\beta_2}(\text{SponsorHHI}^{high}_{c,t-1} \times \text{MarginalB.}) + \boldsymbol{\beta_3}(\text{SponsorHHI}^{low}_{c,t-1}) + \boldsymbol{\beta_4}(\text{SponsorHHI}^{high}_{c,t-1}) + X_{c,t-1} + \delta_{sponsor} + \delta_{Orig.\times St.\times Yr} + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable y_i is a count of the number of differentiated features introduced in the same securitized loan. Differentiation for individual loans is based on any of the following features: Hybrid ARM, Balloon, Interest Only, Negative Amortization, Pay Teaser, Option ARM. Importantly, the empirical strategy includes Originator × State × Year fixed effects, so the identifying variation compares the same originator in the same state at the same point in time, but exposed to differing levels of sponsor competition. The two main variables $\text{SponsorHHI}^{low}_{c,t-1}$ and $\text{SponsorHHI}^{high}_{c,t-1}$ are splines of SponsorHHI, defined using the cutoff point SponsorHHI = 0.1 motivated by Panel (b) of Fig. 6. MarginalBorrower is an indicator for borrowers classified as Subprime and Alt-A. Columns 2–4 include county-level, time-varying controls. Columns 3–4 include loan demand which is measured as the lagged ratio of HMDA applications to HMDA originations in a given county and year. The fixed effects included in each regression are denoted below the regression. Standard errors are clustered at the State × Year level. All variables are defined in Internet Appendix Table IA.B.2.

Table 9
Mortgage denial rates are lowest when high competition targets marginal borrowers.

Spline regression	Denial rates (County-level)		
	(1)	(2)	(3)
$\text{SponsorHHI}^{low} \times$ MarginalB.Share	1.159***	0.721**	0.755***
	(0.320)	(0.307)	(0.288)
$\text{SponsorHHI}^{high} \times$ MarginalB.Share	−0.020	0.048*	0.096***
	(0.021)	(0.029)	(0.033)
MarginalBorrowerShare	−0.098***	−0.075***	−0.080***
	(0.030)	(0.028)	(0.026)
SponsorHHI^{low}	−1.513***	−1.067***	−1.087***
	(0.292)	(0.282)	(0.264)
SponsorHHI^{high}	0.018	−0.038	−0.083***
	(0.019)	(0.026)	(0.031)
Controls	No	Yes	Yes
County FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Observations	7653	7653	7255
R^2	0.844	0.878	0.884

This table reports the results of a spline regression investigating:

$$y_{c,t} = \alpha + \boldsymbol{\beta_1}(\text{SponsorHHI}^{low}_{c,t-1} \times \text{MarginalB.Share}) + \boldsymbol{\beta_2}(\text{SponsorHHI}^{high}_{c,t-1} \times \text{MarginalB.Share}) + \boldsymbol{\beta_3}(\text{SponsorHHI}^{low}_{c,t-1}) + \boldsymbol{\beta_4}(\text{SponsorHHI}^{high}_{c,t-1}) + X_{c,t-1} + \delta_{\text{County}} + \delta_{St.\times Yr} + \epsilon$$

We estimate regressions over the database of securitized mortgages over the period 1997–2008. The dependent variable $y_{c,t}$ is the ratio of number of mortgage applications denied a given County-Year over the total applications in a given County-Year. We perform this regression at the county level because we do not have a direct mapping of ABSNet with HMDA at the loan level. The two main variables $\text{SponsorHHI}^{low}_{c,t-1}$ and $\text{SponsorHHI}^{high}_{c,t-1}$ are splines of SponsorHHI, defined using the cutoff point SponsorHHI $= 0.1$ motivated by Panel (b) of Fig. 6. MarginalBorrowerShare is computed as the share of borrowers classified as Subprime and Alt-A in the ABSNet database. Column (2) includes county loan demand as a control and column (3) includes time-varying county-level characteristics as controls. The fixed effects included in each regression are denoted below the regression. Standard errors are clustered at the State × Year level. All variables are defined in Internet Appendix Table IA.B.2.

Table 10
Delinquencies by product differentiation and securitization cohort.

(Values in $ bn)	Subprime		Alt-A		Prime	
	Standard	Differentiated	Standard	Differentiated	Standard	Differentiated
	(1)	(2)	(3)	(4)	(5)	(6)
Early boom period						
2000	5.64	0.19	0.31	0.03	0.53	0.66
2001	5.46	0.37	3.13	2.98	5.69	1.47
2002	19.39	1.18	2.96	3.68	14.93	19.31
2003	36.8	4.86	7.54	2.23	29.04	26.85
2004	56.0	17.90	10.02	7.34	18.32	42.90
Sub-total	123.29	24.51	23.97	16.26	68.52	91.20
Pre-crisis period						
2005	78.09	58.31	11.85	42.99	15.88	33.47
2006	69.48	132.14	17.50	87.78	11.74	37.48
2007	25.46	75.72	14.06	69.51	9.70	27.92
2008	0.58	0.60	0.02	0.28	0.55	0.62
Sub-total	173.61	266.77	43.43	200.56	37.9	99.49
Total	296.91	291.28	67.40	216.82	106.40	190.68

This table presents the economic significance of delinquencies in the collateral of Subprime, Alt-A and Prime MBS. Note that the years do not refer to the year of delinquency, rather they refer to the year of securitization (deal closing). Values are in billions of dollars based on loan balances at origination. The delinquency amount within each category is further broken down into standard and differentiated collateral. A loan is defined as "Differentiated" if it takes any of the following features: Negative Amortization, Interest Only, Hybrid ARM, Option ARM, Balloon Payment or Pay Teaser. All variables are defined in Internet Appendix Table IA.B.2.

CRediT authorship contribution statement

Peter Haslag: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kandarp Srinivasan:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anjan V. Thakor:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors have nothing to disclose.

Data availability

Replication Program for "Competition, Differentiation and Crises: Evi dence from 18 Million Securitized Loans" (Reference data) (Mendeley Data)

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103947.

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