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Abstract

The 1990s rollout of mortgage automated underwriting systems allowed for complex underwriting rules, cut processing time, and raised house prices substantially. We show that locations exposed to initial adopters of Freddie Mac's Loan Prospector system experienced an early housing boom due to a switch to statistically-informed underwriting rules. Loan Prospector adoption increased lending at high loan-to-income ratios by around 18 per cent. Applying our estimated response to lenders who adopted later, we find that the rollout of new lending standards with the GSEs' systems can explain more than half of U.S. house price growth between 1993 and 2002.

JEL Classification: G21, L85, R21, R31

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1 Introduction

Credit conditions and house price expectations both played some role in the 2000s housing boom and bust, as documented in the literature following Mian and Sufi (2009). However, there is still disagreement about the fundamental cause of the boom. The empirical literature primarily focuses on the 2000s subprime period, studying how various local measures of credit conditions and expectations are related to house price growth after 2002. In contrast, some papers taking a structural modeling approach study late 1990s shocks to credit standards and beliefs (Greenwald (2018); Kaplan, Mitman and Violante (2020); Greenwald and Guren (2021)). This earlier timing lines up better with the start of the boom, and is also informed by aggregate shifts in mortgage characteristics.

In this paper, we first argue that lenders' adoption of automated underwriting systems (AUS) generated a large shift in national lending standards that coincides with the start of the boom. We then directly estimate the causal effect of AUS adoption on mortgage characteristics and house prices using a difference-in-differences approach. We find that AUS adoption did indeed have a large causal effect on house prices. Our estimated response profile is consistent with feedback to house price expectations contributing to the total effect.[1]

Our paper is one of the first to empirically explore the effect of credit conditions on house prices in the mid 1990s – a period of substantial change in the mortgage industry. As well as reducing processing time, the shift to automated underwriting facilitated more complex, statistically-informed underwriting rules. The new underwriting approach propagated nationally with technology adoption, expanding credit access as AUS usage accelerated during the late 1990s refinancing boom. The new rules downplayed the role of current income in future mortgage default, making this a valuable time period to consider when studying how lending standards affect the housing market.[2]

[1] In this regard our findings are in line with Chodorow-Reich, Guren and McQuade (2024), who show that an improvement in fundamentals in the late 1990s together with diagnostic expectations can explain the subsequent boom-bust-rebound in house prices. We identify and estimate the effect of a specific change in fundamentals: automated underwriting technology and show that the empirical response profile is consistent with expectations feedback.

[2] In contrast to most of the empirical housing boom literature, Favara and Imbs (2015) do offer an explanation for house price growth in the late 1990s, arguing that changes in bank branching restrictions can explain a large share of house price growth. We argue that the rollout of AUS is at least as important

By using variation in both lender adoption timing and the characteristics of early underwriting systems, we can separately identify both the effect of new underwriting rules and the effect of automation itself. We find that the introduction of statistically-informed underwriting standards had a large effect on house prices, and can explain at least half of the change in house prices from 1993 to 2002. In contrast, automation by itself did not have a statistically significant effect on house prices.

Our paper highlights a potential trade-off when deciding which factors to rely on in underwriting. Narrative evidence indicates that the shift towards statistically-informed underwriting reduced the emphasis on mortgage payment-to-income ratios because of a weak relationship with default risk.[3] However, the consequence was a large increase in borrowing capacity and house prices in just a few years as lenders rolled out automated underwriting systems. When a small number of underwriting systems are widely used, changes in underwriting rules are highly correlated across lenders. This remains relevant today. In 2023, over 80% of HMDA purchase loans to owner-occupiers of single-family homes were underwritten using Fannie's or Freddie's systems, or the FHA's scorecard.

To implement a difference-in-differences approach, we use press releases to identify initial users of Freddie Mac's system, Loan Prospector (LP), and Fannie Mae's system, Desktop Underwriter (DU). We also leverage differences between the early versions of the two systems to disentangle the effects of automation and statistical underwriting rules. Both Loan Prospector and Desktop Underwriter were publicly released in 1995, with initial users participating in pilot programs starting in 1994 (Maselli (1994); Campbell (1994)). When lenders first started using Loan Prospector, they reported that the system applied standards that differed from Freddie's manual underwriting rules (Maselli, 1994). In contrast, Fannie Mae's Desktop Underwriter system initially just encoded Fannie's manual underwriting rules (Straka, 2000). So while early versions of DU helped to accelerate application processing, lending standards were not directly affected. To address the possibility of endogenous adoption, we show that among initial users of the

as branching regulation, which primarily affects portfolio loans made by commercial banks. Automated underwriting systems were applied by a broader set of institutions to a broader set of loans.

[3] Maselli (1994) and Straka (2000), suggest that the new AUS rules were able to expand credit access without a substantial increase in default risk. The weak relationship between payment-to-income ratios and default has also been well documented in the academic literature. See Foote and Willen (2018) for a review.

systems, the choice of LP or DU reflected whether lenders did more business with Freddie or Fannie prior to the release of the systems.

Comparing initial adopters of LP with initial adopters of DU, we document a credit response consistent with relaxed limits on the ratio of debt payments to income. Using Home Mortgage Disclosure Act (HMDA) data, we find that lenders increased high loan-to-income (LTI) lending by 18 per cent (from an initial level of 15 per cent of the market) after adopting Loan Prospector. This increase was broad-based, with middle and high-income borrowers also borrowing more relative to their income. Using a smaller sample taken from the ICE McDash mortgage servicing data (which does not identify the lender), we verify that a 1 standard deviation increase in county exposure to initial LP adopters leads to an increase in high debt-to-income (DTI) lending of around 1 percentage point, and that the relaxation was initially specific to borrowers making a down payment of at least 20 per cent of the property value.[4]

Finally, we estimate the effect on house prices. We find that one standard deviation (3.6 percentage point) increase in the market share of early Loan Prospector adopters leads to an additional $1\frac{1}{2}$ percentage points of house price growth between 1993 and 1997. We also compute a back-of-the-envelope effect on national house prices. The calculation applies our house price response estimates for early Loan Prospector adopters to the aggregate increase in usage of both GSEs' systems, taking into account the fact that DU also started to apply statistical rules in the late 1990s. Usage increased substantially during the late 1990s refinancing boom, and the cumulative effect on house prices between 1993 and 2002 is around 24 per cent, or around three quarters of the change in U.S. real house prices over the same period. Using exposure to initial Desktop Underwriter adopters, we show that automation absent a change in lending standards has little effect on house prices.

Our paper contributes to two strands of the mortgage and housing literature. First, we contribute to the literature exploring the causal origins of the 2000s housing boom.[5] Our

[4]The (back-end) debt-to-income ratio is the ratio of monthly debt payments and other financial obligations to gross monthly income. The loan-to-income ratio is the ratio of loan size to annual income. In our setting, the key underwriting variable was likely DTI rather than LTI. However, our main analysis focuses on the LTI ratio, as data on DTI ratios is limited during our sample period and not available at the individual lender level (LTI generates a consistent ranking to DTI when holding interest rates and non-mortgage obligations fixed, but in practice variation in both rates and other obligations mean that LTI is a noisy measure of DTI).

[5]Adelino, Schoar and Severino (2012); Albanesi, DeGiorgi and Nosal (2022); Di Maggio and Kermani

empirical setting predates much of the reduced-form work examining the housing boom. For example, Adelino, Schoar and Severino (2016); Foote, Loewenstein and Willen (2020), Mian and Sufi (2009), and others, study lending patterns in the early 2000s, whereas we focus on the 1990s. Our sample period overlaps with Favara and Imbs (2015), who argue that bank branching deregulation was an important driver of house price growth in the late 1990s and early 2000s. The adoption of AUS likely affected an even larger part of the market. The removal of branching restrictions only directly affected commercial banks, but lenders of all types adopted the GSEs' systems.

Foote, Loewenstein and Willen (2019) present an institutional framework around 1990s technological innovation in the mortgage market. They discuss narrative evidence that DTI ratios at origination became less important in lending decisions over this period and show that the relationship between mortgage size and income gradually weakened. Based on the timing of these aggregate changes, they suggest a connection to the 1995 release of Fannie and Freddie's AUS. However, Foote et al. (2019) claim that house prices were not affected, pointing to the absence of stronger relative house price growth in low-income zip codes during 1990s. In contrast, we directly estimate large effects of AUS on house prices using a difference-in-differences approach. We find that the credit expansion was broad-based and not clearly stronger for low income households.

In contrast to much of the empirical literature, papers taking a structural approach typically model the effect of changes occurring in 2000 or earlier.[6] Of these, Greenwald (2018), Greenwald and Guren (2021) and Kaplan et al. (2020) specifically model the effect of a sudden relaxation of payment-to-income limits in the late 1990s, but do not provide a fundamental explanation for that shift. We argue that the acceleration of AUS adoption during the late 1990s refinancing boom provides an explanation for this shift in payment-to-income limits. Ferreira and Gyourko (2011) note that while some markets experienced a housing boom starting in the mid to late 1990s, other markets did not boom until much later. We show that counties with high exposure to initial users of Loan Prospector experienced an earlier boom. Dokko, Keys and Relihan (2019) distinguish between early and late booming markets, and provide evidence that the late boom was closely linked to

(2017); Griffin, Kruger and Maturana (2021); Landvoigt, Piazzesi and Schneider (2015), among others.

[6]Some examples are: Favilukis, Ludvigson and Van Nieuwerburgh (2017); Greenwald (2018); Greenwald and Guren (2021); Justiniano, Primiceri and Tambalotti (2019); Kaplan et al. (2020)

the adoption of non-traditional mortgage products. In this paper, we show that financial innovation, in this case, statistical lending standards, is also important for the early boom.

Our paper also contributes to a growing literature on fintech in the mortgage industry. Fuster, Plosser, Schnabl and Vickery (2019) and Buchak, Matvos, Piskorski and Seru (2018) study the post-crisis period and emphasize the convenience of fintech lenders. Fuster et al. (2019) document the processing advantages offered by fully online applications. The effect of automated underwriting is a related but distinct question (for example, automated underwriting is also used by lenders who do not offer fully online applications). We show that the adoption of automated underwriting systems primarily affected the housing market through a change in lending standards rather than processing advantages.

2 Institutional background

2.1 Early automated underwriting systems and their usage

In the early 1990s, most mortgage applications were manually underwritten using guidelines set out by lenders, the GSEs, or other secondary market participants. This reliance on human underwriters posed personnel challenges when dealing with large fluctuations in application volumes, for example during refinancing booms (Straka, 2000). Manual underwriting also arguably limited the time available to spend on difficult files. Automation was, therefore, expected to deliver benefits to both lenders and borrowers.

The potential benefits of AUS went beyond processing. Historically, lenders had based their underwriting rules on direct experience – for example, observed poor performance of loans with low down payments (Straka, 2000). Subsequent increases in standardization, data availability and computing power facilitated sophisticated statistical analysis of the determinants of mortgage default. Automated underwriting systems not only made these complex, statistically-informed rules easier to apply, but they also allowed for proprietary algorithms. A lender could use another party's system without observing the underlying rules directly.

Freddie Mac was at the forefront of loan performance analysis and incorporated new statistical rules when it developed its Loan Prospector system. Early in 1994 a number of lenders participated in a pilot program, and, in 1995, Loan Prospector was publicly released.[7] Fannie Mae's system Desktop Underwriter was also piloted and released along a similar timeline. While Desktop Underwriter had the potential to reduce processing times, it was initially not statistically based. Instead, the system simply applied Fannie Mae's existing manual guidelines (Straka (2000); Nixon (1995)).[8]

During our sample period, the GSEs' systems were used to determine eligibility and did not provide lenders with a detailed risk measure (Temkin, Johnson and Levy, 2002). For most applications, Loan Prospector generated one of only two recommendations "accept" and "caution". Loans with a "caution" recommendation could be found to be eligible but would need to be manually underwritten.[9] Risk-based pricing was rare in the 1990s, with most lenders using average cost pricing and charging all their borrowers the same rate. The market was segmented into prime and subprime lenders, with subprime lenders charging higher rates to all borrowers reflecting higher average risk. Specialized subprime lenders showed little initial interest in the GSEs' systems because they were thought to be less applicable to high-risk borrowers. Temkin et al. (2002) provide an extensive discussion of the GSEs' eventual move into subprime lending and the potential of their systems to be used for risk-based pricing. These developments occurred after the end of our sample period.

The GSEs marketed Desktop Underwriter and Loan Prospector as general underwriting tools, and lenders also used them for loans they did not intend to sell to Fannie or

[7] Freddie Mac was also active in promoting the use of FICO scores around the same time, publishing a study in 1992 showing that general FICO scores had substantial predictive power for mortgage default. While general credit scores ultimately became input into Loan Prospectors' recommendations, Freddie Mac also strongly recommended the use of credit scores to lenders using manual underwriting. The take-up of credit scores as an underwriting input during this period was, therefore, not unique to lenders using the GSEs' automated underwriting systems. Fannie Mae also soon followed suit in recommending the use of FICO scores in manual underwriting (Pierzchalski, 1996).

[8] Some large lenders and mortgage insurers also developed systems around this time. The Countrywide Loan Underwriting Expert System (CLUES) was one of the earliest systems used on a large scale and was rolled out in 1993. The rules used by CLUES were developed not through statistical analysis, but by observing the decisions of expert underwriters. Countrywide started developing the system in 1991 with the primary goal of increasing the number of loans per employee – not changing lending standards (Talebzadeh, Mandutianu and Winner, 1995). PMI Mortgage Insurance Co. had been working on its Automated Underwriting Risk Analysis (AURA) system since the 1980s. Unlike CLUES, the system was statistically based and generated a risk score between 1 and 100 (Mikel and Baker, 1992).

[9] For government loans (i.e. FHA or VA loans) Loan Prospector generated either an "accept" or "refer" recommendation. Loans receiving a "refer" recommendation also needed to be manually underwritten in order to be eligible (Temkin et al., 2002).

Freddie. Some lenders reported running every application through LP or DU, and then manually underwriting applications that were not accepted (LaMalfa (1998); LaMalfa (1999); LaMalfa (1999); Jones (1997)). The GSEs' underwriting guidelines represented an industry standard that was widely used for both portfolio loans and loans sold to other secondary market participants. This gave the GSEs' systems a competitive advantage. According to Dennis and Robertson (1995):

> To a great extent, the underwriting guidelines of both Fannie Mae and Freddie Mac are the core standards that most lenders attempt to follow. Even those lenders who don't intend to sell loans to these two secondary mortgage market players should attempt to follow these well-conceived underwriting guidelines. (pp. 116-117)

The ability to automatically certify that a loan met the GSEs' standards was valuable to lenders. An "accept" recommendation from the GSEs' AUS could arguably be taken as a general indication that the loan was prime. While competing systems were able to automatically underwrite loans using Fannie or Freddie's public manual rules, the ability to sell certain loans was tied to the GSEs proprietary automated rules, and therefore to the use of Fannie or Freddie's underwriting systems.

2.2 Effect on lending standards

Freddie's statistical approach to lending standards had the potential to expand credit access without a substantial increase in default risk. Credit access could in principle be expanded in a low-risk way by optimizing underwriting cutoffs and allowing for more complex interactions of risk factors. AUS made these interactions of risk factors easier to apply, and removed the need to directly disclose underwriting rules.[10] Unlike Freddie's manual rules, which were public, Loan Prospector applied a proprietary algorithm. Our understanding of how standards changed therefore relies on narrative evidence from lenders who used the systems.

Lenders' comments to trade journals point to an expansion along the debt-to-income dimension subject to other risk factors. A debt-to-income expansion was first noted in

[10] More information on the performance of GSE scorecards can be found in Straka (2000), Gates, Perry and Zorn (2002) and Foote et al. (2019).

1994 by lenders participating in the Loan Prospector pilot (Maselli, 1994). Harney (1996) reports that the system accepted debt-to-income ratios up to 72 per cent, at a time when manual underwriting guidelines typically limited the debt-to-income ratio to less then 36 per cent (Maselli (1994), Irwin (1992)), with some discretion.[11] Both Harney (1996) and Maselli (1994) suggest that LP eligibility at high debt-to-income ratios was initially limited to borrowers with offsetting factors, such as a good credit, low loan-to-value ratio or substantial cash reserves. In contrast, public GSE data show that by 1999 high debt-to-income ratios were allowed in a much broader range of cases by both Fannie and Freddie.[12] Although the data from this period are not detailed enough to "back out" precise changes in underwriting standards, we document responses consistent with a large relaxation of debt-to-income limits.

2.3 Adoption timing

Table 1 provides statistics on lenders' usage of the GSEs' systems over time. In the first half of 1997, less than a quarter of eligible loans were processed using Desktop Underwriter or Loan Prospector (Foster, 1997). Adoption increased substantially for both systems after 1997, coinciding with a refinancing boom. Historically, lenders needed to hire a large number of additional underwriters to cope with refinancing demand, so AUS offered substantial benefits during these periods (according to Talebzadeh et al. (1995), Countrywide's development of CLUES was motivated by a 'serious shortage of qualified underwriters' during the previous refinancing boom).

Why were lenders slow to adopt the GSEs' systems? Trade journals highlight a number of concerns that lenders had. Even the initial DU and LP users we focus on here acknowledged it would take some time for the gains to be realized. For example, a representative of Flagstar Bank noted that "It isn't cheap: there are transaction costs, equipment costs, training costs. And there's a learning curve. The efficiencies are starting

[11] For context, around 7 per cent of 2018 HMDA applications had a debt-to-income ratio above 60 per cent (the ratio is top-coded at 60 per cent), with most being denied. We expect that a limit of 72 per cent would not be binding in most cases. In contrast, around 58 per cent of 2018 HMDA applications had a debt-to-income ratio above 36 per cent. These statistics are based on the subset of HMDA applications for which the debt-to-income ratio is known. We use 2018 data as prior years did not contain information on the debt-to-income ratio.

[12] See Bergquist (2001) and Temkin et al. (2002) for more information about the GSEs' later expansion into 'A-' lending.

to materialize now" (LaMalfa, 1996). A representative of InterFirst stated, "We love LP, but it's still not cost-effective" (LaMalfa, 1997). Another lender noted that after licensing and usage fees Loan Prospector "doesn't appear to net any cost saving", with the caveat that "the Freddie Mac and Fannie Mae processes can ultimately decrease your cost in volatile periods" (LaMalfa, 1996). In November 1995, the per loan cost of a Loan Prospector approval was around $400 (Sullivan, 1995).[13] The GSEs also used proprietary data standards (Markus, Dutta, Steinfield and Wigand, 2008) and according to Oliver and McDonald (1997) lenders "did not make full use of AU systems (i.e., use AUS at the point of sale) owing in part to lack of integration with back-end systems".

Furthermore, Freddie would not accept a DU decision and Fannie would not accept a LP decision. This lack of reciprocity meant that lenders would need to run a loan through both LP and DU to compare pricing, paying double the fees (Foster, 1997). Many lenders felt it was too costly to use multiple systems, and either chose just one of the GSEs' systems or continued to apply the GSEs' manual guidelines (possibly using an alternative system). Perceived costs of switching and the fact that the systems locked them into a buyer led to lenders having sticky relationships with either Fannie or Freddie (DeMuth (1999); Johnson (2020)). Switching costs may also have led some lenders to strategically delay adoption.

According to the GSEs' annual reports, usage of DU and LP stabilized at just over 60 per cent in 2001 (Table 1). This is likely an underestimate of overall AUS usage and the prevalence of relaxed DTI rules. Starting in the late 1990s, both Fannie and Freddie made agreements with some very large sellers to purchase loans underwritten using other systems. The GSEs' Single Family Loan Performance datasets show that high DTI loans continued to be purchased from the sellers with whom the GSEs' had made agreements to accept alternative systems. Prior to these agreements, Freddie Mac was predicting higher stabilized LP usage of 80–85 per cent. Reported usage of DU and LP by larger community banks in 2004 was also around 85 per cent – consistent with the GSEs' original forecasts (Costanzo, 2004).

[13] Sullivan (1995) provides some pricing details disclosed by Fannie and Freddie, but it is not possible to do a full cost comparison. Although Freddie's per loan fees were slightly higher, Fannie charged a number of additional fees that were not disclosed.

3 Data and descriptive statistics

We use data on mortgage lending from the Home Mortgage Disclosure Act (HMDA). HMDA provides fairly comprehensive coverage of the U.S. mortgage market, particularly for properties located in metropolitan areas. The dataset includes mortgage originations and loan purchases, as well as applications that did not lead to an origination.[14]

We supplement the HMDA data with ICE McDash mortgage servicing data – a loan-level dataset with information obtained from a number of large servicers. ICE McDash covers a variety of loan types, including portfolio loans, agency loans, non-conventional loans and subprime loans. The dataset provides information on key underwriting variables such as credit score, debt-to-income and loan-to-value ratio as well as the property zip code. It does not contain information on the lender. While the dataset starts in 1992, coverage of certain variables is limited early in the sample. Loan performance data is sparse prior to the late 1990s so the dataset cannot be used for default analysis over our sample period. We use FHFA county price data to study the effect on house prices.[15]

3.1 Lender statistics

Table 2 lists initial users of Loan Prospector or Desktop Underwriter. These lenders were already using the systems at the time of public release in 1995. We identify HMDA IDs associated with these lenders based on their names and locations provided in the source articles. We also use NIC data on institutional relationships and transformations to ensure that the set of HMDA IDs we use for each lender captures as consistent an institution as possible over our sample.

Because DU initially applied Fannie's manual rules, we can use initial users of DU as a control group to quantify the effect of adopting statistical lending standards. As both groups of lenders adopted an AUS at the same time, the direct effect of automation is differenced out. Any remaining selection concerns relate to the choice of LP relative to DU, rather than the decision to adopt an AUS early. Below we show that the choice

[14] We also use confidential supervisory data collected under the HMDA to construct a measure of processing time from application dates and closing/decision dates. The confidential dataset contains more comprehensive information than what is disclosed in the public version of the data.

[15] We also explored other house price indices but found them to be less reliable and with lower effective coverage than the FHFA county house price indices during the 1990s.

between LP and DU is driven by relationships lenders had with Fannie or Freddie before the development of the systems, rather than anticipation of the different rules applied by LP.

Table 3 shows statistics by lenders' choice of system. The main difference between initial LP and DU users is that lenders choosing LP sold a much larger share of their loans to Freddie prior to the release of the two underwriting systems. Consistent with Freddie's historic association with thrifts, early LP users are more likely to be thrifts or thrift subsidiaries than DU users. Table 4 reports estimates from a linear probability model relating lenders' choice of system to the variables in Table 3. Each variable is divided by its standard deviation. Research conducted by Mortech in 1996 "revealed that AU decisions are primarily based on which GSE the lender does the most business with" (Strickberger, 1999).[16] Table 4 supports this, as lenders selling a larger share of loans to Freddie (rather than Fannie) from 1991-1993 are much more likely to be initial users of Freddie's system LP. Coefficients on other variables, including LTI, are insignificant.

3.2 County statistics and exposure measure

Table 5 shows county statistics by exposure to initial Loan Prospector users, for all counties and for counties with exposure above and below the median. In Section 4.3, we use variation in county exposure to initial adopters of Loan Prospector to study the effect on county house prices:

$$EarlyLP_c = \frac{\text{\# Loans reported in county } c \text{ by LP lenders (Table 2; Column 1)}}{\text{\# Loans reported in county } c \text{ by all HMDA reporters}} \quad (1)$$

We also report estimates conditional on total exposure to early adopters of either Loan Prospector or Desktop Underwriter:

$$EarlyAUS_c = \frac{\text{\# Loans reported in county } c \text{ by all lenders in Table 2}}{\text{\# Loans reported in county } c \text{ by all HMDA reporters}} \quad (2)$$

[16]Consistent with this, a representative of Fleet Mortgage stated in 1999 that: "It is impractical for us to have two AU systems" and "we elected to go with DU first. We typically sell about 60 per cent of our business to Fannie Mae. That had a lot to do with it." (DeMuth, 1999).

Conditioning on $EarlyAUS_c$ is consistent with the loan-level analysis where we compare loans made by initial LP users with initial DU users (rather than all other lenders). However, this approach also reduces precision. We obtain broadly consistent results under both approaches.

Ideally, we would compute market shares (1) and (2) using data from before lenders started using the systems. However, some lenders in Table 2 failed to report property locations for a large share of their loans during this period. Prior to 1996, depository institutions were only required to report locations for properties in MSAs where the lender had a home or branch office.[17] From 1996 onward, banks or thrifts with at least \$250 million in assets (or that were subsidiaries of a holding company with banking or thrift assets of least \$1 billion) no longer received exemptions from reporting property locations, and, as shown in Figure B.1, location reporting improved considerably.[18]

We therefore construct (1) and (2) using 1996 data, when coverage increases because of new reporting requirements. This also means that loans will not be selected based on proximity to branches. However, defining the exposure measure after the release of the systems does raise the concern that adoption caused lenders to disproportionately expand their market share in areas already experiencing strong price growth (in contrast to directly causing higher price growth). Given this concern, we verify in the appendix that the effect on house prices is robust to computing exposure using 1993 data.

Even if the adoption of Loan Prospector were random at the lender level, county-level exposure might still be correlated with location characteristics that drive different house price growth over the sample. Figure 1A shows combined county market shares of initial LP users. In our analysis we focus on a specification that uses census division by time fixed effects. Figure 1B shows the distribution of the county market share of initial Loan Prospector users relative to the census division average. Table 6 shows the relationship between exposure to early Loan Prospector users and several county characteristics. Both

[17]This did not include offices of affiliates such as brokers or correspondents, or non-branch locations which accepted applications. Non-depositories were considered to have a branch office in any MSA where they had at least 5 reportable loans or applications for home purchase or home improvement in the previous calendar year, and therefore reported locations for a larger share of loans.

[18]Figure B.1 also shows that the share of loans without a location increased substantially for early adopters specifically during the period when they first started using the GSEs' systems (1994–1995) and before new reporting rules. Given location reporting requirements prior to 1996, this could reflect an increase in lending further from the lenders' branch locations.

dependent and independent variables are normalized by dividing by the standard deviation. Table 6 also shows relationships before and after controlling for $\text{EarlyAUS}_{c,1996}$. There are some statistically significant relationships between county characteristics and the exposure measure. In county-level analysis we therefore condition on the variables in Column 1 interacted with time dummies. Our results are robust to including or excluding $\text{EarlyAUS}_{c,1996}$. This is reassuring as conditioning on $\text{EarlyAUS}_{c,1996}$ substantially changes some of the correlations with observed county variables.

We further show in Section 4.3 that areas more exposed to initial Loan Prospector adopters did not experience different price growth before 1994, and actually experienced weaker price growth after 2000. This is consistent with our claim that additional price growth in the mid 1990s is due to early adoption of statistical underwriting criteria, not due to other characteristics of these lenders or the areas in which they operate. For example, if the affected lenders were in general more aggressive, their locations may be expected to experience stronger price growth during the later part of the boom as well. In fact, we observe the opposite. Weaker price growth after 2000 for early adopters relative to other lenders is consistent with other lenders catching up once they, too, adopt similar automated underwriting systems.

4 Results

4.1 Credit response

In this section, we measure how the new rules rolled out with Loan Prospector influenced lending. We compare loan characteristics of initial LP users with initial DU users before and after 1994, differencing out the effects of automation alone. Using HMDA, we find that initial LP adopters lend more relative to income. Using ICE McDash, we find an increase in high DTI lending, and suggestive evidence that the DTI expansion was initially limited to borrowers making a substantial down payment.

We look at a fairly narrow window around the 1994 adoption year. As we move further in time from the press releases listing initial adopters, the less likely it is that these lenders exist throughout the HMDA sample. We create consistent institutions over the 1992-1997 period to account for mergers and acquisitions. DU also started to apply very similar rules to LP after 1997. This means longer-run difference-in-differences estimates could be smaller than the full effect, though this depends on whether DU users rolled out the system at scale and kept using it. Feedback effects, for example through house price expectations, may also mean that differences persist even after the two systems became more closely aligned. We elaborate on this in Section 5.1.

First, we look at the effects on high loan-to-income lending. We define $HighLTI_i$ equal to one if the loan-to-income ratio exceeds 2.5 and zero otherwise. We estimate the approximate proportional response using Pseudo Poisson Maximum Likelihood.[19] We include county-year and income quartile-year fixed effects. For loan i reported by lender l in income quartile n in county c in year t:

$$HighLTI_i = \exp\left(\alpha_{l,n} + \gamma_{n,t} + \delta_{c,t} + \sum_{k \neq 1993} \mathbb{1}_{t=k}\beta_k LP_l\right) + \epsilon_i \tag{3}$$

where LP_l is an indicator equal to one for early LP users and zero for early DU users. β_k is interpreted as the log change in number of loans between the base year (1993) and year k.

We focus on a loan-to-income ratio cutoff of 2.5, as this approximately corresponds to the manual underwriting DTI cutoff of 36 per cent for a household with a relatively high level of existing debt payments. Setting the LTI cutoff too high may understate the effect of the new rules on households with high levels of other debt, as these households have a lower level of LTI at a given DTI.[20] Figure 2A shows that the high LTI loan share increases

[19]Unlike linear regression where the dependent variable is the log of the outcome of interest, Pseudo Poisson Maximum Likelihood gives consistent estimates in the presence of heteroskedasticity and avoids dropping observations where the outcome is equal to zero (Wooldridge (2010); Cohn, Liu and Wardlaw (2022)).

[20]To inform the cutoff, we looked at data on components of the DTI ratio from the mid 1990s. Property taxes in the 1995 Survey of Consumer Finances average around 1.3 per cent of the property value, and homeowner's insurance in the 1995 American Housing Survey averages around 0.45 per cent of the property value. The average 30 year mortgage rate in 1995 was around 8 per cent. At a loan-to-value ratio of 80 per cent, the debt-to-income ratio is then approximately:

$$\begin{aligned} DTI &= \frac{OtherObligations}{Income} + \left(\frac{1.3+0.45}{0.8} + 1200 \times \frac{\frac{0.08}{12}\cdot(1+\frac{0.08}{12})^{360}}{(1+\frac{0.08}{12})^{360}-1}\right)\cdot LTI \\ &= \frac{OtherObligations}{Income} + 8.805 \cdot LTI \end{aligned}$$

A household with an LTI of 2.5 will therefore have a DTI of around 36 per cent if their other financial obligations, such as debt payments and child support, are around 14 per cent of income. This is about the 90th percentile of other financial obligations for households in the 1995 Survey of Consumer Finances who by around 18 per cent following adoption. Using linear regression we find a 3 percentage point increase in the high LTI share of originations (Figure B.2A).

To show how responses vary with borrower income we further interact LP_l with indicators for each income quartile n and include county by income quartile by year fixed effects. Low income households are not necessarily the only beneficiaries of expanding debt-to-income limits, especially where the expansion is conditional on other risk factors. If housing demand and down payments scale with income (and the mortgage is the primary source of debt) we might expect both the numerator and the denominator of the DTI ratio to increase at a similar rate with income. In recent HMDA data the DTI distribution is very similar for households in the bottom three-quarters of the income distribution, and high DTI borrowing spans the entire income distribution (Appendix Figure B.3). Consistent with this, we find that the response is not limited to lower income households (Figure 2B). The percentage point response is shown in Figure B.2B.

Figure 2C shows approximate percentage effects on the average loan-to-income ratio. Average LTI increases gradually with a peak effect of about 8 per cent in 1997, and again we see responses across the income distribution (Figure 2D). Overall, we do not find evidence of larger effects for households in the bottom income quartile and conclude that the shift to statistical lending standards led to a broad-based increase in credit access.

As HMDA does not contain information on DTI during our sample period, we supplement our analysis with ICE McDash data. This dataset provides us with additional variables, but it also has limitations we would like to be upfront about. We do not observe the lender, and therefore rely on the local exposure measure described in Section 3 rather than directly comparing loans made by LP and DU users. Loan characteristics are also frequently missing during our sample period.[21] Given these limitations, we view the ICE McDash analysis as providing suggestive support for our other estimates.

We use the following specification, where loan i is secured by a property in county c, in census division d:

bought their home in the last 5 years.

[21] Credit scores were not as widely used for mortgage underwriting at the start of our sample period and conditioning on non-missing credit score reduces the sample size considerably. We therefore do not condition on credit score. In some cases, the debt-to-income ratio reported may be the front-end ratio rather than the back-end ratio. The front-end ratio considers only the mortgage payment, property taxes and insurance, whereas the back-end ratio includes payments on other debts as well as other obligations such as alimony and child support payments.

$$HighDTI_i = \delta_c + \gamma_{d,t} + \sum_{k=1994}^{1997} \mathbb{1}_{t=k} \left(\beta_k EarlyLP_c + \alpha_{1,k} X_c + \alpha_{2,k} X_i \right) + \epsilon_i \tag{4}$$

$EarlyLP_c$ is the county market share of initial Loan Prospector adopters defined in Section 3. Our sample period here is June 1993-1997. We drop loans originated before June 1993 because the share of loans with missing DTI is very high prior to this time. We flexibly control for the loan-to-value ratio and loan source (e.g. retail origination, servicing rights purchased). $HighDTI_i$ is equal to one if loan i has a DTI ratio above 36 per cent. As outlined in Section 2, a DTI limit of 36 per cent was seen as standard for manually underwritten loans in the early 1990s. However, underwriters had some discretion to approve loans with higher DTI ratios in the presence of compensating factors, so this should not necessarily be interpreted as a hard cutoff.[22]

Figure 3A shows that a one standard deviation increase in the market share of initial LP users leads to a peak increase of just over 1 percentage point in the share of loans with DTI ratio above 36 per cent. This is a large response relative to the overall share of loans with a DTI ratio in this range, which was $7\frac{1}{2}$ per cent in 1993. The estimates are similar when including county controls interacted with year dummies. Figure 3B shows that the expansion in lending at high DTI ratios was initially limited to loans with a down payment of at least 20 per cent. For this subset of loans the peak effect on DTI is closer to 2 percentage points. There is some evidence that this requirement was later relaxed, consistent with Freddie Mac increasing DTI limits for a broader set of borrowers.

Additional tests

We report a number of additional results in the appendix. We look at effects on lending volumes, but are unable to use location fixed effects given that the location of the property is missing for a large share of HMDA loans prior to 1996. We estimate the approximate percentage change in the number of loans made by lender l in income quartile n in year t using Pseudo Poisson Maximum Likelihood:

$$\#Loans_{l,n,t} = \exp\left(\alpha_{l,n} + \gamma_{n,t} + \sum_{k \neq 1993} \mathbb{1}_{t=k} \beta_k LP_l \right) + \epsilon_{l,n,t} \tag{5}$$

[22] For example, in Stamper (1995), Freddie Mac provides an example of how credit scores could be used by manual underwriters to support a debt-to-income ratio of 41 per cent.

Appendix Figure B.4A plots estimates of $\{\beta_k\}$ from Equation 5. Initial LP adopters start to grow originations relative to initial DU adopters in 1994. The cumulative log change peaks at 0.846 in 1995, meaning the number of loans made by early Loan Prospector adopters was about 133 per cent higher in 1995 than 1993 (relative to the corresponding change for initial DU adopters). The response is large, but it could reflect initial LP users expanding at the expense of other lenders, and does not necessarily represent loans that would not otherwise have been made. Without location by year fixed effects, the response also reflects feedback effects from the housing market. The change in lending volumes is similar across income quartiles (Appendix Figure B.4B) and for purchase and refinance loans (Appendix Figure B.5).

We also repeat our main analysis without conditioning on location. The responses are qualitatively similar but larger. As with the volume response, this could reflect county-level feedback effects from stronger house price growth to credit demand. This feedback channel should be mostly absorbed by county-year fixed effects in our main specification (Appendix Figure B.6).

We verify that the results are not driven by a single lender by re-estimating coeffients dropping each lender in turn. The responses are fairly robust across all variables (Appendix Figure B.7).

4.2 Processing time response

We adopt a different empirical approach to quantify effects on processing time, as this requires comparing initial users of the GSEs' AUS with other lenders. Comparing lenders who chose to participate in the GSEs' pilot programs with other lenders raises the possibility of selection. To mitigate this we construct a control group of three matched lenders for each initial DU and LP user. There is a large pool of potential control lenders to choose from. The matching procedure targets three variables with the goal of finding lenders with similar business models in 1993: the share of refinance loans, the share of originations held in portfolio and the share of loans that were purchased (rather than originated).[23] For purchase application i in income quartile n submitted to lender l with

[23] We do not condition on variables that are only available for depository institutions as several of the initial AUS users are mortgage companies. We also only match to lenders in the same broadly-defined size class, based on the combined number of originations and loan purchases.

action a taken in year t we estimate:

$$Time_i = \alpha_{l,n,a} + \gamma_{g(l),a,t} + \beta_0 AUS_l + \beta_1 DU_l \cdot Post_t + \alpha_1 X_i + \epsilon_i \quad (6)$$

where $Time_i$ is the number of days between application and closing for originated loans, and the number of days between application and denial for denied application. Actions a include origination and denial. Lender group $g(l)$ includes lender l as well as the three matched control lenders. AUS_l is an indicator equal to one for initial DU or LP adopters and zero for control lenders. $Post_t$ is an indicator equal to one for years after 1993 (the sample period is 1992-1997). We exclude FHA and VA loans. We condition on log loan amount and log income. In specifications with only originated loans we also include loan purchaser type fixed effects.

Table 7 shows estimates of β_1 from Equation 6. The time from application to closing/denial declines by about 2 days relative to matched lenders. When we estimate Equation 6 separately for originated and denied loans we find a processing time reduction of about 2 and 5 days, respectively.[24] This effect is smaller than the 9 day reduction in processing time for purchase applications to 'Fintech' lenders documented by Fuster et al. (2019), and considerably smaller than potential reductions from AUS that were projected in the mid 1990s (Maselli, 1994). Fuster et al. (2019) focus on lenders with a fully online application process, which is a different technology than AUS (it is likely that most 'non-Fintech' lenders in their sample use an AUS too given the recent setting).

Our historical setting is useful for measuring the effect of AUS on processing time, despite the fact that more recent HMDA data provide information about whether and which AUS was used for a given loan. This is because AUS usage is now widespread and its use for a given application is likely subject to considerable selection bias. To illustrate this, we re-estimate Equation 6 with 2018-2019 HMDA data and replace AUS_l with an indicator for whether an AUS was actually used to underwrite application i (i.e. AUS_i). Appendix Table B.1 shows that AUS usage is associated with a four day *increase* in processing time

[24] We find no significant effect on processing time for refinance applications. This could reflect differences in the way lenders use the systems or process these loans. Lenders and borrowers may also have more incentive to complete a purchase loan transaction as fast as possible given deadlines associated with the property transaction.

on average. Conditional on denial, processing time increases by 11 days. This could be because denials following AUS usage are more likely to occur for reasons that emerge later in the process. Conditional on origination, AUS usage is associated with a 3 day reduction in processing time – similar to what we find in our historical setting.

Overall, we find that AUS allows for faster denials and modestly reduces total processing time for originated loans as well. This suggests the automated task accounts for a fairly small proportion of work that needs to be done to successfully close the loan.

4.3 House price response

Next we estimate the effect on house prices. We start by plotting price growth since 1993 for counties with very high and very low exposure to Loan Prospector (Figure 4A). The housing boom started earlier in high exposure counties, but these counties also experienced weaker growth during the 2000s. The difference in the price profiles for the two sets of counties is large – peaking at over 10 percentage points.

To estimate the response, we compare counties with different exposure to initial LP adopters, conditional on the county characteristics in Table 6 interacted with year dummies:

$$\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{t=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{t=k}\left(\beta_k \frac{EarlyLP_c}{SD(EarlyLP_c)} + \alpha_k X_c\right) + \epsilon_{c,t} \tag{7}$$

where $\log(Price_{c,t})$ is the log of the FHFA county house price index and $EarlyLP_c$ is the measure of county exposure to early LP adopters defined in Section 3 (using Poisson regression instead has a negligible effect on the estimates). We include county and census division by year fixed effects, and divide the exposure measure by its standard deviation, so the coefficient of interest β_k is interpreted as the cumulative house price response to a one standard deviation increase in exposure. We also use a similar specification to compare counties with high exposure to initial DU users relative to matched control lenders.

A one standard deviation increase in exposure to Loan Prospector (3.6pp) raises prices by around 0.8 per cent in 1996 with a peak (cumulative) effect of 1.85 per cent (Figure 4B). The house price response grows for several years after the original shock. Some further relaxation in the rules applied by LP is consistent with the credit analysis and narrative evidence, though this seems unlikely to fully account for the long-run response. Price momentum is another explanation, for example, through feedback channels such as adaptive expectations (Armona, Fuster and Zafar (2019); Bailey, Cao, Kuchler and Stroebel (2018); Case, Shiller and Thompson (2012)). We explore this channel further in Section 5.1 below.

Figure 4C further conditions on the county share of lenders who were either early DU or early LP adopters, $EarlyAUS_c$. This specification is more consistent with the approach in Section 4.1, where we compare loans made by initial LP adopters with loans made by initial DU adopters. However, conditioning on the combined share removes some variation in exposure and the estimates are somewhat less precise. Using this specification, a one standard deviation increase in exposure has a peak cumulative effect on house prices of 1.4%. Neither specification exhibits a significant pre-trend, which helps to address concerns about correlations with other county-level factors driving house price growth.

We also estimate the house price response following the adoption of Desktop Underwriter, which initially only automated Fannie Mae's existing manual underwriting rules. To mitigate selection bias we use the matched lender approach from Section 4.2. Figure 5 plots estimates of $\{\beta_k\}$ from:

$$\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{k=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{t=k}\Big(\beta_k EarlyDU_c + \alpha_k X_c\Big) + \epsilon_{c,t} \tag{8}$$

Where X_c includes the combined market share of initial DU users and matched control lenders. Estimates for initial LP users using the same matched lender approach are shown on the same graph. To compare the effects of DU and LP we do not normalize by the standard deviation of the respective exposure measures here, so $\{\beta_k\}$ is interpreted as the effect of moving from a share of zero to a share of one:

$$\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{k=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{t=k}\Big(\beta_k EarlyLP_c + \alpha_k X_c\Big) + \epsilon_{c,t} \tag{9}$$

Exposure to initial DU users leads to an insignificant increase in house prices, smaller in magnitude than the effect of exposure to initial LP users. We do see more substantial effects on house prices at longer horizons, with exposure to either initial DU or initial LP users having a similar effect by 2004. This is consistent with DU also incorporating new statistical underwriting rules by the late 1990s.

Additional tests
We estimate similar responses when computing exposure using 1993 data (prior to adoption). The 1993 measure effectively excludes activity by depository institutions in locations where they did not have physical branches (Appendix Figure B.8). We also test whether the house price response is driven by a single lender. To do this, we construct alternative measures of $EarlyLP_c$ and $EarlyAUS_c$, dropping each lender sequentially. Dropping individual lenders does not qualitatively change the main result (Appendix Figure B.9). Finally, we plot the relationship between 1993-1996 house price growth and the county exposure measure conditional on a number of county characteristics. The relationship between the exposure measure and house price growth looks broadly linear (Appendix Figure B.10). We also repeat the analysis with the log price-to-wage ratio as the dependent variable. We compute annual per capita wage and salary income at the county level using BEA data. The estimates are broadly unchanged, indicating that local house prices rise considerably relative to incomes (Appendix Figure B.11).

5 Magnitude and Timing of House Price Response

To better compare our estimates with other studies, we compute the elasticity of county house prices to credit. This requires us to estimate county-level credit responses. Given changes to HMDA location reporting rules over our sample, we do not estimate the response of aggregate lending and instead focus on the average loan-to-income ratio and share of high LTI loans. Table 8 shows changes in the county high LTI share and average LTI from 1993-1996 corresponding to a one standard deviation increase in exposure, along with the corresponding effect on county house prices. One standard deviation of exposure is 0.036, or 3.6 percentage points.[25] Average LTI increases by 1.7-1.9 per cent depending on the specification. The high LTI share increases by 0.5 percentage points.

[25] We restrict the sample to counties with at least 250 home purchase originations in 1993. Average LTI in particular is quite noisy for counties with a small number of loans. The estimated effect on the high LTI share is also very similar in the full sample. We focus on the 1993-1996 change in order to mitigate selection as initial AUS users were less likely to report the property county in 1994 and 1995 (Figure B.1). In 1996 HMDA location reporting rules were tightened and missing location shares declined.

Given a cumulative one per cent effect on house prices over the three years, a one per cent increase in average LTI translates into around an 0.15 per cent average annual increase in house prices over the first three years. The magnitude of the response is therefore broadly similar to estimates of the response of house prices to mortgage credit obtained in other settings, such as Loutskina and Strahan (2015) and Favara and Imbs (2015) (see Greenwald and Guren (2021) for a summary).[26]

Next we interpret the timing of the response. Across multiple specifications, we show that the house price response takes a long time to unwind. In fact, prices continue to diverge for several years across more and less exposed locations. Could this plausibly be a response only to AUS adoption? A key point is that most lenders did not adopt Fannie and Freddie's systems until several years after public release. Based on Fannie and Freddie's aggregate adoption statistics (Appendix Table 1), early adopters should have substantially higher usage of the systems than other lenders until at least 1998. We therefore expect the fundamental AUS-induced gap in lending standards to remain in place for a few years, but to gradually close by the early 2000s. Broadly consistent with this story, the difference in house prices across these areas does eventually decline. That is, locations exposed to early Loan Prospector users experienced an earlier housing boom, but other locations catch up.

A long-lived effect is therefore not that surprising. What is arguably more surprising is that the medium-run effect is much larger than the initial effect, with house prices continuing to diverge for several years. Next, we propose an explanation based on feedback to expectations and demonstrate its plausibility using a simple theoretical framework. We show that combining adaptive expectations with the short-run response can approximately replicate our entire price response profile.

5.1 Can Expectations Feedback Explain the Price Response Profile?

We now combine our short-run estimates with some assumptions to construct a predicted price profile under adaptive house price expectations. Intuitively, households in more exposed locations observe higher recent house price growth following AUS adoption. If

[26] Loutskina and Strahan (2015) find an elasticity of house price to loan volumes of 0.133 over one year. Favara and Imbs (2015) find an elasticity of house prices to loan volumes over one year of 0.134, and Greenwald and Guren (2021) find an elasticity of 0.133 at the same horizon.

these households naively extrapolate, past growth lowers their perceived cost of housing and increases housing demand on top of the initial direct effect of AUS adoption.

We assume that the price response up until 1995 is the direct effect of AUS adoption. Starting in 1996, we update expectations according to an adaptive rule. We also estimate the housing supply response using the Census Building Permits Survey and incorporate this when updating house prices. By assumption, the house price response is zero up until 1993, and then matches the estimated price effect to 1995. The fundamental difference in lending standards then gradually unwinds with adoption in the 'control' group, so that any further expansion in the price response comes from expectations feedback only.

Housing demand

We assume nominal housing demand of unconstrained households with income y_i is given by:

$$P \cdot H_i = \frac{\alpha_i y_i}{\theta + r + \delta - g^e} \tag{10}$$

That is, each (unconstrained) household has a constant housing budget share equal to α_i. The denominator on the right hand side of 10 is the user cost: θ is property taxes and insurance as a share of property value; r is the mortgage interest rate, which we also assume is equal to the opportunity cost of home equity for convenience; δ is the depreciation rate; and g^e is expected annual house price growth.

Next we compute aggregate nominal housing demand. For this we also need to consider the demand of households who are constrained. We denote the observed housing budget share by $\hat{\alpha}_i$. For unconstrained households $\alpha_i = \hat{\alpha}_i$, but for constrained households $\alpha_i > \hat{\alpha}_i$. For simplicity we assume $y_i = \bar{y}\ \forall i$:

$$P \cdot H = P \sum_{i=1}^{N} H_i = N \frac{\bar{y} \frac{\sum_{i=1}^{N} \hat{\alpha}_i}{N}}{\theta + r + \delta - g^e} = N \frac{\alpha \bar{y}}{\theta + r + \delta - g^e} \tag{11}$$

From here on we use α to denote the aggregate observed housing budget share.

Using the short-run price response to back out the change in fundamentals

When a Loan Prospector allows households to borrow more relative to their income, this increases α and, therefore, housing demand. We take our estimated short-run price response and use it back out the implied change in α for 'treated' locations. We distinguish between 'treated' locations ($\tilde{\alpha}$) and control locations (α). We start with the following decomposition of the change in log nominal housing demand:

$$\Delta \log(PH) = \Delta \log P + \Delta \log H \tag{12}$$

We then substitute our estimated short-run price and housing supply responses as follows (where $\hat{\beta}^P_{1995}$ is from Equation 4 and $\hat{\beta}^H_{1995}$ is described when we discuss calibration below):

$$\Delta_{1993-1995} \log(PH) = \hat{\beta}^P_{1995} + \hat{\beta}^H_{1995} \tag{13}$$

Assuming that there is no short-run effect on the user cost $\theta + r + \delta - g^e$, we use $\Delta \log(PH) = \Delta \log(\alpha)$ combined with a calibrated value for $\alpha_{1993}(= \tilde{\alpha}_{1993})$ to obtain $\tilde{\alpha}_{1995}$. We then keep $\tilde{\alpha}_t = \tilde{\alpha}_{1995}$ up until 2002. That is, we assume our natural experiment generates a one-off permanent relaxation of borrowing constraints between 1993 and 1995 for the 'treated' group. We further assume that the 'control' group adopts in line with national GSE statistics on the share of loans underwritten using AUS s_t (Table 1). That is:

$$\alpha_t = (1 - s_t)\alpha_{1993} + s_t \tilde{\alpha}_t, \ \forall t \geq 1996 \tag{14}$$

House price growth expectations

Beginning in 1996, we update households' growth expectations. We assume that households form expectations at the start of year t about price growth during the year as follows:

$$g^e_t = \lambda \sum_{j=1}^{t-t_0} (1 - \lambda)^{j-1} g_{t-j} \tag{15}$$

As we will be making a comparison with our difference-in-differences estimates, we next rewrite Equation 15 to separate out the part of expectations that comes from the 'treatment'. We denote expectations in the 'treated' location by $\tilde{g}^e_t$ and write it as a function of our estimated price response Effect_t (expressed as an annual percentage change):

$$\tilde{g}_t^e = \lambda \sum_{j=1}^{t-t_0} (1-\lambda)^{j-1} g_{t-j} + \lambda \sum_{j=1}^{t-t_0} (1-\lambda)^{j-1} \text{Effect}_{t-j} \Rightarrow \tilde{g}_t^e \qquad = g_t^e + \Delta_t \tag{16}$$

That is, expectations in the 'treated' location are equal to expectations in the 'control' location plus $\Delta_t = \lambda \sum_{j=1}^{t-t_0} (1-\lambda)^{j-1} \text{Effect}_{t-j}$. Recalling our estimated responses are cumulative log changes, we compute the annual percentage price response as:

$$\text{Effect}_t = e^{\frac{\hat{\beta}_t}{\hat{\beta}_{t-1}}} - 1 \tag{17}$$

Implied difference-in-differences house price response

Next, we compute the cumulative implied (difference-in-differences) effect on nominal housing demand relative to 1993:[27]

$$\Delta \log(PH)_t = \log\left(\frac{\tilde{\alpha}_t}{\alpha_t}\right) + \left[\log(\theta_t + r_t + \delta - g_t^e) - \log(\theta_t + r_t + \delta - g_t^e - \Delta_t)\right] \tag{18}$$

The first term on the right hand side of Equation 18 is the direct effect due to AUS adoption. This diminishes over time due to gradual adoption in the 'control' group (Equation 14). The term in square brackets reflects feedback to growth expectations. Finally, we combine Equations 12 and 18 with our estimated supply response to back out the cumulative log price response at the end of year $t \geq 1996$:

$$\Delta \log P_t = \Delta \log(PH)_t - \Delta \log H_t = \Delta \log(PH)_t - \hat{\beta}_t^H \tag{19}$$

[27]In 'treated' locations the cumulative log change in demand is: $\log y + \log(\frac{\tilde{\alpha}_t}{\tilde{\alpha}_{1993}}) + \log(\theta_{1993} + r_{1993} + \delta - g_{1993}^e) - \log(\theta_t + r_t + \delta - g_t^e - \Delta_t)$. In 'control' locations the cumulative log change in demand is: $\log y + \log(\frac{\alpha_t}{\alpha_{1993}}) + \log(\theta_{1993} + r_{1993} + \delta - g_{1993}^e) - \log(\theta_t + r_t + \delta - g_t^e)$. Taking the difference between treated and control locations gives $\log(\frac{\tilde{\alpha}_t}{\alpha_t}) + [\log(\theta_t + r_t + \delta - g_t^e) - \log(\theta_t + r_t + \delta - g_t^e - \Delta_t)]$ (Equation 18).

5.2 Calibration

Growth expectations (λ, g_t^e)

Our goal here is to show that our estimated response profile *could* be generated from a one-off relaxation of constraints due to AUS adoption. We perform a search for the value of the expectations parameter λ that best matches our response profile using a least squares criterion. For each value of λ, we first compute g_t^e using the FHFA U.S. All Transactions HPI before computing $\Delta \log P_t$ as described above.[28] We find that $\lambda = 0.098$ best matches the data response profile.

Non-growth user cost components (θ_t, r_t, δ)

We use data on property tax and insurance costs from the American Housing Survey to calibrate θ_t. We divide each household's total property tax and insurance costs by their property value and set θ_t equal to the average value for owner-occupiers. $\theta_{1993} = 0.018$ and is broadly similar over the sample period. We assume an interest rate (and opportunity cost of home equity) equal to the prevailing Freddie Mac interest rate on a 30-year fixed rate mortgage. This is 7.31% in 1993.[29] We assume an annual depreciation rate of $\delta = 0.02$.

Initial housing budget share (α_{1993})

We compute $\alpha = \frac{P \cdot H}{y} \cdot (\theta + r + \delta - g^e)$. We set $\frac{P \cdot H}{y}$ equal to the 1993 AHS average house price to income ratio of 3.12. We use θ_{1993}, r_{1993} δ and g_{1993}^e as described above. This gives us $\alpha_{1993} = 0.18$.

Housing supply response ($\hat{\beta}_t^H$)

We use Census data on permits issued for new housing units to estimate the supply response using 7 with $\log(Permits_{c,t})$ as the dependent variable. We use building permits data as we only observe the outstanding housing stock at the 1990 and 2000 censuses.

[28] When computing g_t^e using observed price data, we use a modified formula is needed so that weights sum to one when working with a finite price history: $g_t^e = \frac{\lambda}{1-(1-\lambda)^{t-t_0}} \sum_{j=1}^{t-t_0} (1-\lambda)^{j-1} g_{t-j}$. As we have price data back to 1975, the difference relative to Equation 15 is not very large by the mid 1990s.

[29] The timeseries can be downloaded here: https://fred.stlouisfed.org/series/MORTGAGE30US.

While there is an increase in the flow of building permits, the annual estimates are statistically insignificant. Nonetheless, we use the point estimates to calibrate the model (assuming no supply response would lead to a larger house price effect). We convert the flow estimates into the cumulative percentage change in implied total housing units. The cumulative increase in outstanding housing stock from 1993 to 2003 is 0.65%. This implies a decade housing supply elasticity of 0.9. While this is somewhat lower than the MSA elasticities estimated in Saiz (2010); our period of analysis is also shorter than the 30-year period used there. We note that recently Baum-Snow and Han (2024) have estimated more modest supply elasticities from 2000 to 2010.[30]

5.3 Results

Figure 6 compares our estimated response from Figure 4B (solid line) with the response generated by applying adaptive expectations to the short-run effect (dashed line). We are broadly able to match the shape of the data response.[31] Although the model generated response is conditional on a number of strong simplifying assumptions, we believe this exercise enhances the plausibility of our main estimates. It also illustrates how our reduced form total response could reflect a fundamental direct response combined with feedback through an expectations channel, consistent with Chodorow-Reich et al. (2024).

6 Back-of-the-envelope aggregate effect

So far we have presented house price estimates normalized by the standard deviation of county exposure to initial LP users. Extrapolating to 100 per cent exposure implies a very large effect on house prices, with important aggregate implications.

We combine the estimated price response with aggregate AUS usage statistics from Table 1 to compute a cumulative aggregate log price response from 1993 to 2002:

$$\hat{G} = \sum_{k=1994}^{2002} s_{1994+(2002-k)} \hat{\beta}_k \tag{20}$$

[30] Both annual and cumulative estimates are included in the online appendix in Figures B.14A and Figure B.14B.

[31] Our ability to match the data response using adaptive expectations is robust to different assumptions about adoption rates in the control group, though slower control group adoption implies lower values of λ.

where $\{\hat{\beta}_k\}$ are the estimated coefficients from Equation 9 and s_k is the share of lenders adopting AU in year k, constructed using statistics from Fannie and Freddie's annual reports shown in Table 1. Fannie and Freddie report the share of purchases underwritten using their systems, and we compute s_k as the annual increase in those numbers. In applying these weights to our estimated coefficients, we implicitly use this as a measure of the total market share of lenders using the systems.

Table 9 shows that national adoption of LP and DU can explain 44-77 per cent of aggregate price growth depending on assumptions.[32] Our estimates may be more credible closer to 1994, so we show the effect of using different response horizons. For example, in row 1 of Table 9 we only use $\hat{\beta}_{1994}$ and $\hat{\beta}_{1995}$ to compute the aggregate response. We assume that the price effect is permanent (at least until 2002), and so the cumulative response is equal to $\hat{\beta}_{1995}$ at longer horizons. Even when cutting off the response at this shorter horizon, DU and LP adoption can still explain a substantial portion of aggregate price growth.

Our calculation assumes that the response estimated for early LP users can also be applied to DU users after DU rolled out similar rules to LP. That is, we think of 'adoption' as the adoption of statistical underwriting standards for this exercise. We do not know exactly when this happened as we do not have loan level data that allows us to directly observe the DTI distribution for lenders using LP and lenders using DU over time. However, we do observe the DTI distribution for loans purchased by Fannie and Freddie starting in 1999 (Figure B.12) and note that the two distributions look very similar. Given the more widespread usage of DU and LP by 1999, this tells us that DU and LP were likely doing very similar things at this point in time. This indicates that DU's change in standards happened sometime before then. Moving across the columns of Table 9, our results are not very sensitive to the assumed timing of the DU change. This is because an additional year or two of response time does not have a large effect (and has no effect when we constrain the maximum response to occur at a 2 year horizon).

Equation 20 further assumes that the response profile for later adopters is the same as for the initial adopters and that the response estimated using variation in adoption across counties can be applied at a national level. These are strong assumptions and $\hat{G}$ should

[32] We compute the percentage price response as $100 \times (e^{\hat{G}-\frac{1}{2}\hat{\sigma}^2_{\hat{G}}} - 1)$ as recommended by Kennedy (1981). In this case adjusting for the variance of $\hat{G}$ makes very little difference.

be interpreted with these caveats in mind. Nonetheless, we think it is entirely plausible that the shock we document could have large aggregate effects.

A primary concern with aggregation in our setting relates to the supply of funds. If lending standards are relaxed but the supply of funds is fixed, it is expected that aggregate interest rates will rise. If true, we might still expect to see divergence in local house prices due to differences in local lending standards, but with a smaller effect on national prices. Justiniano et al. (2019) consider this argument and note that the empirical facts suggest an expansion in the supply of funds over the housing boom period. Such an expansion of funds, for example due to securitization or a global savings glut, would allow changes in lending standards to have large aggregate effects on house prices. We also note that agency MBS has broad appeal both in the U.S. and internationally. A large expansion in GSE lending criteria need not necessarily imply a large increase in mortgage rates.

7 Conclusion

We use the 1990s rollout of the GSEs' automated underwriting systems to study the effects of AUS on processing time, lending standards, and house prices. Automation coincided with the adoption of statistically-informed underwriting rules. Freddie Mac's system Loan Prospector allowed households to take on larger mortgage payments relative to income, and Fannie Mae soon incorporated similar rules into Desktop Underwriter. We find that counties with early exposure to these rules experienced an early housing boom starting in around 1995. The new rules propagated nationally as more lenders adopted the GSEs' systems over the second half of the 1990s. We speculate that the switch to statistically-informed rules can explain more than half of aggregate U.S. price growth in the early stages of the 2000s housing boom.

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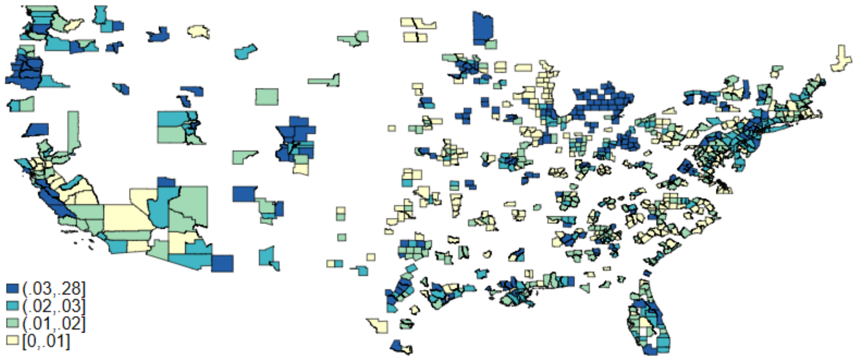
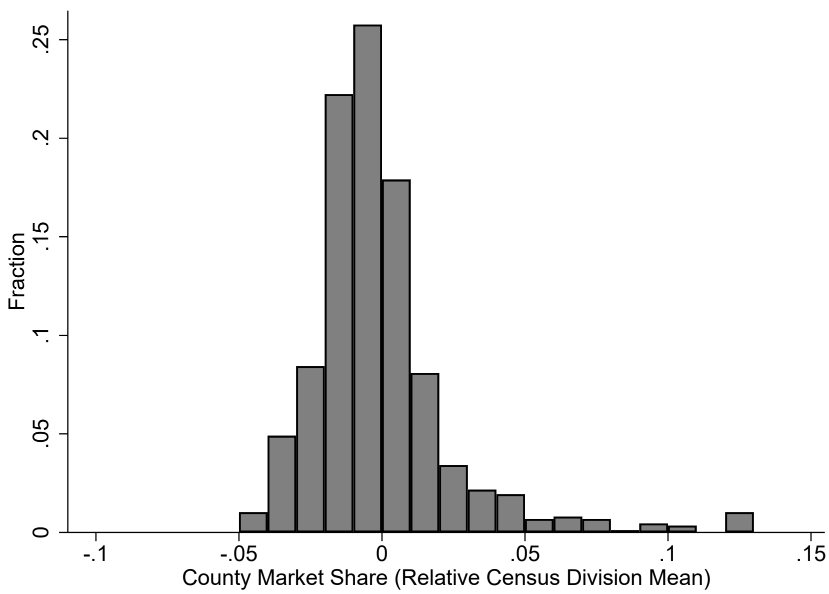
FIGURE 1

MARKET SHARE OF INITIAL LOAN PROSPECTOR USERS

Panel A.



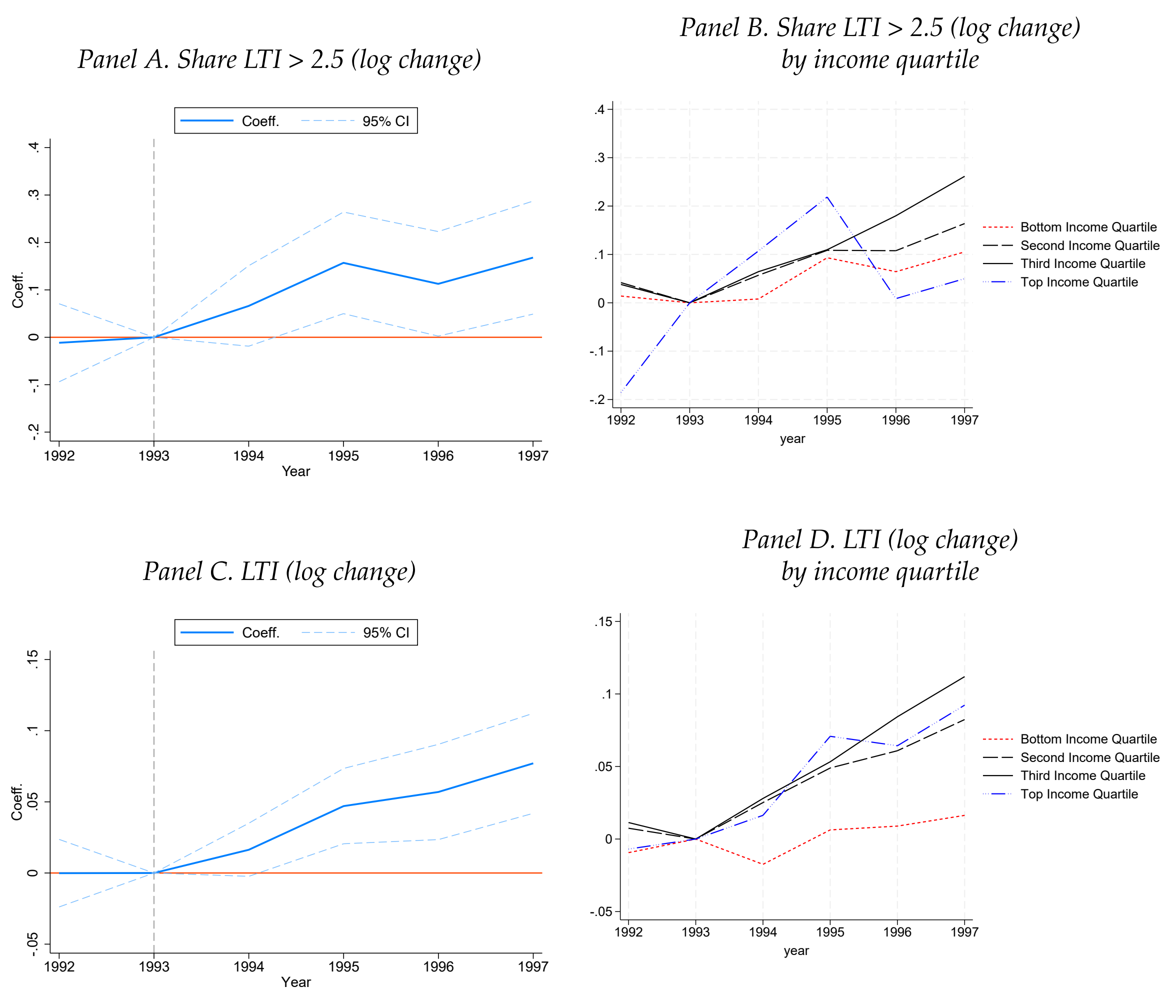
Panel B.



NOTES: Panel 1A maps the exposure measure: $EarlyLP_c = \frac{\text{\# Loans reported in county } c \text{ by LP lenders in Table 2}}{\text{\# Loans reported in county } c \text{ by all HMDA reporters}}$. Market shares are computed using 1996 HMDA originations and purchases and include both purchase and refinance loans. The sample includes counties in metropolitan areas with non-missing house price data. Panel 1B shows variation in the exposure measure relative to the census division average. The relative market shares in Panel 1B are winsorized at the 99th percentile. Sources: HMDA and authors' calculations.

FIGURE 2

MORTGAGE CREDIT OUTCOMES FOR INITIAL LOAN PROSPECTOR USERS
(RELATIVE TO INITIAL DESKTOP UNDERWRITER USERS)

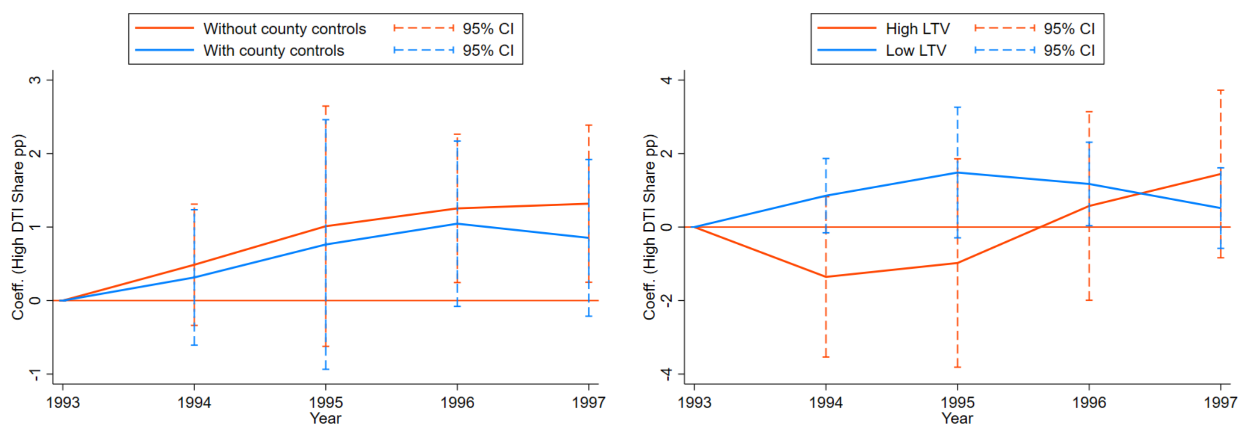


NOTES: Figure 2A plots estimates of $\{\beta_k\}$ from Equation 3 where the dependent variable is an indicator equal to one for originations with a loan-to-income ratio (loan size divided by income) above 2.5 and zero otherwise. Figure 2B plots the response by borrower income quartile. Figure 2C plots estimates of $\{\beta_k\}$ from Equation 3 where the dependent variable is the LTI ratio. Figure 2D plots the response by borrower income quartile. The sample is HMDA purchase and refinance originations reported by initial users of Loan Prospector or Desktop Underwriter. We identify mergers and acquisitions using the NIC (National Information Center) and combine these into a single institution throughout the entire sample period. The coefficients are interpreted as changes relative to 1993. Standard errors are clustered by lender $\times$ income quartile. Sources: HMDA and authors' calculations.

FIGURE 3

EFFECT OF COUNTY EXPOSURE TO INITIAL LOAN PROSPECTOR USERS ON HIGH DTI SHARE

Panel A. Overall effect on share DTI > 36 *Panel B. Overall effect on share DTI > 36 by LTV*

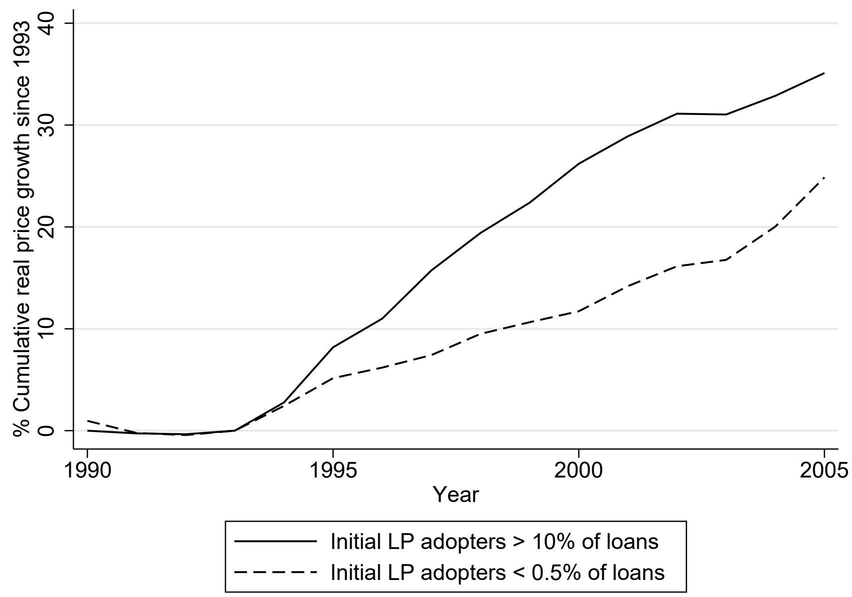


NOTES: Figure 3A plots estimates of $\{\beta_k\}$ from Equation 4. In Figure 3B we split the sample by the loan-to-value ratio. 'High LTV' loans have an LTV ratio above 80 per cent (i.e. down payment of less than 20 per cent). 'Low LTV' loans have an LTV ratio of 80 per cent or below (i.e. down payment of at least 20 per cent). The average high DTI share in 1993 was around $7\frac{1}{2}\%$. The sample is restricted to conventional loans. High DTI share is the share of loans with DTI>36% (i.e. the GSEs' traditional cutoff). Controls included in all specifications are LTV group by year fixed effects, data source by year fixed effects and the combined county early DU/LP share. Figure 3A shows the estimates with and without additional county level controls interacted with year dummies (coastal indicator, log personal income per capita, the share of originations sold to either Fannie or Freddie, log number of lenders, large lender market share, the ratio of housing costs to income, log median property value, share with a bachelors degree or higher). Standard errors are clustered by CBSA. Sources: ICE McDash; HMDA; 1990 decennial census; BEA; NOAA list of coastal counties; and authors' calculations.

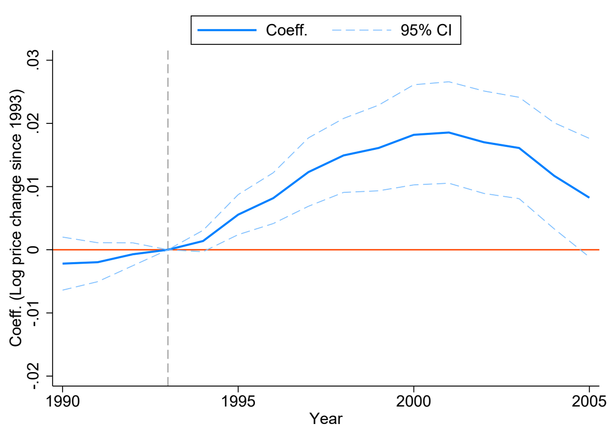
FIGURE 4

Effect of county exposure to initial Loan Prospector users on house prices

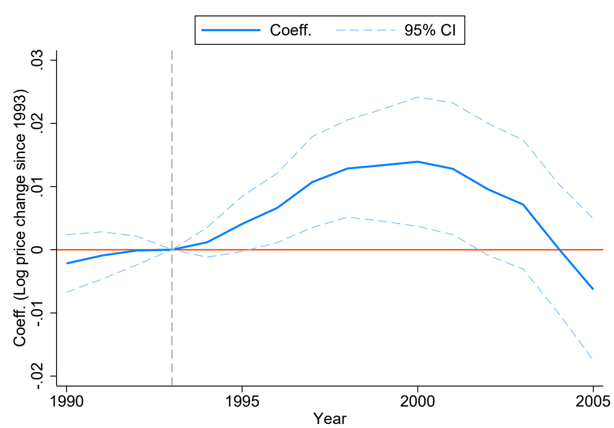
Panel A. The housing boom started earlier in exposed areas



Panel B. Cumulative response relative to all lenders



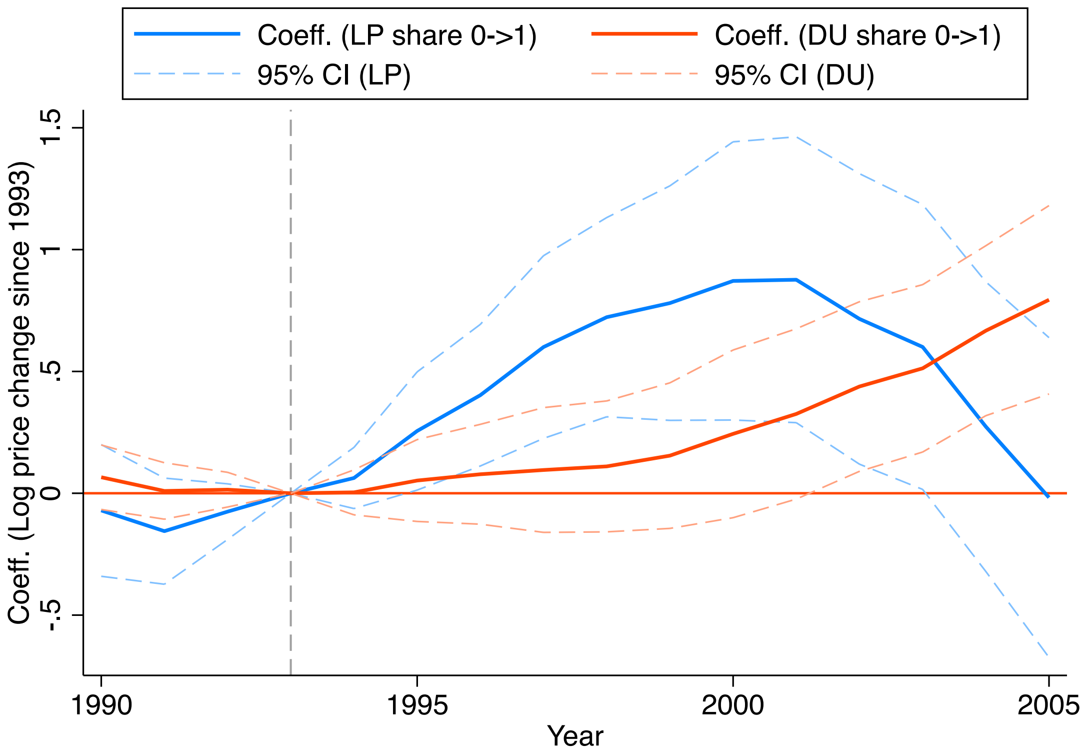
Panel C. Cumulative response relative to DU users



Notes: Figures 4B and 4C plot estimates of $\{\beta_k\}$ from Equation 7. Both 4B and 4C condition on the following county variables interacted with year dummies: coastal indicator, log personal income per capita, share of originations sold to either Fannie or Freddie, log number of lenders, large lender market share, ratio of housing costs to income, log median property value, share with a bachelors degree or higher. Estimates in Figure 4C are also conditional on the combined county share of initial DU and LP users $EarlyAUS_c$. Coefficients are interpreted as cumulative log price changes relative to 1993. Standard errors are clustered by CBSA. The sample is restricted to counties in metropolitan areas with non-missing house price data. Sources: FHFA HPI; HMDA 1990 decennial census; BEA; NOAA list of coastal counties; and authors' calculations.

FIGURE 5

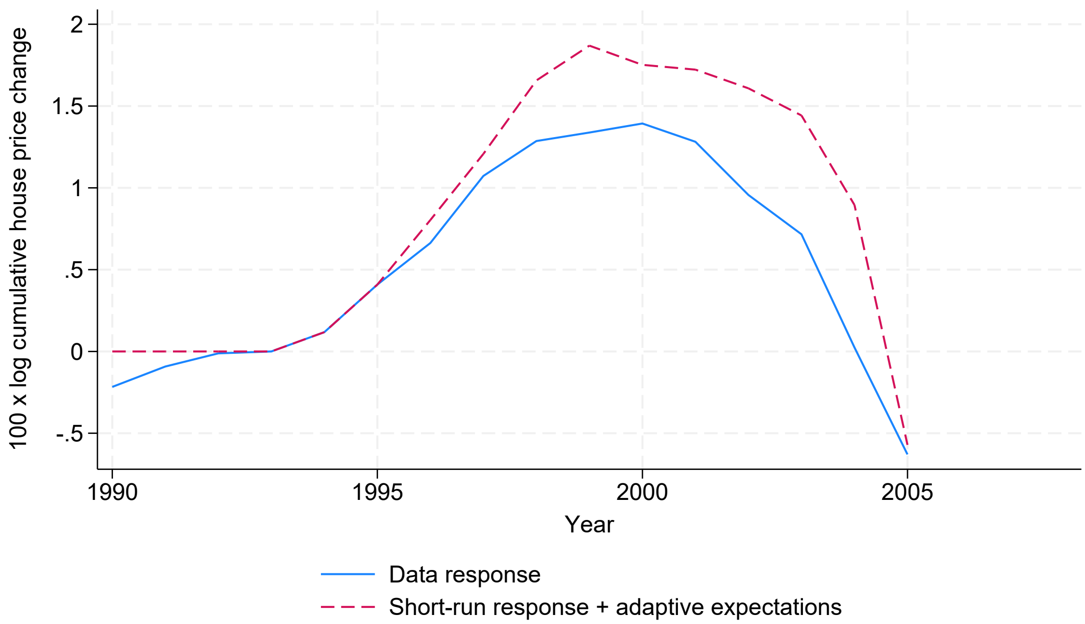
EFFECT OF COUNTY EXPOSURE TO INITIAL DESKTOP UNDERWRITER USERS ON HOUSE PRICES



NOTES: Figure 5 plots estimates of $\{\beta_k\}$ from: $\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{k=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{k=t}\Big(\beta_k Exposure_c + \alpha_k X_c\Big) + \epsilon_{c,t}$, where $Exposure_c$ is either $EarlyLP_c$ (blue line) or $EarlyDU_c$ (red line). $EarlyDU_c$ is the market share of initial DU users and is defined analogously to $EarlyLP_c$. We condition on the following county variables interacted with year dummies: coastal indicator, log personal income per capita, the share of originations sold to either Fannie or Freddie, log number of lenders, large lender market share, the ratio of housing costs to income, log median property value, share with a bachelors degree or higher. Estimates are also conditional on the combined county share of initial users (of DU or LP) and their matched control lenders. Coefficients are interpreted as cumulative log price changes relative to 1993. Standard errors are clustered by CBSA. The sample is restricted to counties in metropolitan areas with non-missing house price data. Sources: FHFA HPI; HMDA; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

FIGURE 6

EXPLAINING THE LONG-RUN PRICE RESPONSE WITH ADAPTIVE EXPECTATIONS



NOTES: The blue line in Figure 6 shows the data response from Figure 4B. The red line plots the price response implied by (1) the short-run estimated price response (to 1995); (2) adaptive expectations applied to the short-run response from 1996 onwards; (3) the housing supply response estimated from data on building permits over the entire sample (4) gradual AUS adoption in the 'control' group in line with national GSE statistics (Table 1). Expectations are updated according to an adaptive expectations rule with parameter $\lambda = 0.098$.

TABLE 1

% OF GSE PURCHASES PROCESSED USING DESKTOP UNDERWRITER OR LOAN PROSPECTOR

	Fannie Mae		Freddie Mac	
	Report	Other	Report	Other
1995				
1996			25	
1997	9		22	54*
1998	22	26*	36	
1999	39		50	>75**
2000	56		56	
2001	59		62	
2002	60		60	
2003			64	
2004			61	

NOTES: This table shows the share of Fannie's purchases processed through DU and the share of Freddie's purchases processed through LP. The table includes numbers from the GSEs' annual reports and numbers reported by Fannie and Freddie representatives to trade journals. The discrepancies these two sources could reflect fluctuations in LP and DU usage within the calendar year, and differences between projected and realized usage. In particular, there is evidence that both Fannie and Freddie projected usage of 80-85% by 1999. These rates were apparently never realized, though during 1999 Freddie stated that over 75% of its purchases were processed through LP. Later annual reports suggest that DU and LP usage stabilized at a lower rate of around 60 per cent because both Fannie and Freddie made agreements with large lenders which allowed them to use alternative systems. Sources: Fannie Mae and Freddie Mac annual reports.

* Wilson, Caroline (1998). Automated Underwriting Goes Mainstream. America's Community Banker, 7(4):36; Gallaher, Douglas (1998). Getting a Payoff from Technology. Mortgage Banking, 58(6): 66–76.

** Murin, Joseph (1999). A Business Transformed by Technology. Mortgage Banking, 60(1): 152.

TABLE 2

INITIAL USERS OF FREDDIE MAC AND FANNIE MAE'S AUTOMATED UNDERWRITING SYSTEMS

Loan Prospector (Freddie Mac)	Desktop Underwriter (Fannie Mae)
Citicorp Mortgage	American City Mortgage Corp.
First Security Savings Bank (Flagstar Bank)	BancBoston Mortgage Corp.
Midland Financial Mortgages (Amerus)	BrooksAmerica Mortgage Corp.
Mission Hills Mortgage Corp.	Crestar Mortgage Corp.
Monument Mortgage	Crossland Mortgage Corp.
Mortgage America	Fleet Mortgage Corp.
Old Kent Mortgage Co.	Headlands Mortgage Co.
PHH Mortgage Corp.	ICM Mortgage Corp. (Pulte Mortgage)
Standard Federal Bank (InterFirst)	National Pacific Mortgage Corp.
	Phoenix Mortgage and Investment
	Residential Funding Corp. (GMAC-RFC)
	Seattle Mortgage Co.
	State Savings Bank
	Temple-Inland Mortgage Corp.
	Trustmark National Bank
	Universal American Mortgage Co.
	Washtenaw Mortgage Co.

NOTES: This table shows early Loan Prospector and Desktop Underwriter users. The two lists were obtained from American Banker (1995) and (PR Newswire, 1995). We track mergers, acquisitions and name changes over the sample period using data from the National Information Center (NIC). We exclude West Jersey Community Bank, which was acquired by Sovereign Bank early in our sample period. Flagstar Bank was an initial user of both LP and DU. We exclude Flagstar from the set of Desktop Underwriter adopters as they reported relying mainly on Loan Prospector up until at least the late 1990s (LaMalfa (1997); LaMalfa (1998); LaMalfa (1999)).

TABLE 3

LENDER CHARACTERISTICS BY SYSTEM

	All	LP Users	DU Users
Share sold to Freddie	0.36	0.51	0.24
	(0.43)	(0.30)	(0.24)
Average loan-to-income ratio	1.45	2.14	1.91
	(0.73)	(1.20)	(0.37)
Portfolio share	0.54	0.23	0.23
	(0.35)	(0.32)	(0.29)
Thrift or thrift subsidiary	0.30	0.22	0.11
	(0.46)	(0.44)	(0.32)
Share bottom quartile income	0.23	0.18	0.14
	(0.14)	(0.11)	(0.08)
Share LTI > 2.5	0.10	0.17	0.22
	(0.11)	(0.13)	(0.13)
Conventional share of originations	0.89	0.86	0.78
	(0.21)	(0.16)	(0.20)
Refinance share of originations	0.67	0.62	0.59
	(0.20)	(0.14)	(0.17)
Number of Observations	4,134	9	18

NOTES: This table shows descriptive statistics for lenders listed in Table 2. Flagstar (an initial user of both systems) is included in Column 2 and excluded from Column 3. Share sold to Freddie is $\frac{\text{\#Loans Sold to Freddie}}{\text{\#Loans Sold to Fannie or Freddie}}$. Portfolio share is the share of loans originated by the institution which were not sold in the the calendar year of origination. Sources: HMDA and authors' calculations.

TABLE 4

HOW IS SYSTEM CHOICE RELATED TO LENDER CHARACTERISTICS?

Dependent variable: Indicator equal to 1 for LP users and 0 for DU users.	(1)	(2)
Share sold to Freddie	0.33**	0.57**
	(0.13)	(0.21)
Average loan-to-income ratio		0.10
		(0.18)
Portfolio share		0.11
		(0.14)
Thrift or thrift subsidiary		-0.14
		(0.13)
Share bottom quartile income		0.04
		(0.29)
Share LTI $>$ 2.5		-0.19
		(0.17)
Conventional share of originations		0.06
		(0.17)
Refinance share of originations		-0.24
		(0.20)
Number of Observations	27	27

NOTES: This table shows estimated coefficients from $\text{LP}_l = \alpha + \beta X_l + \epsilon_l$. LP_l is an indicator equal to 1 for initial Loan Prospector users listed and zero for initial Desktop Underwriter users (see Table 2). Flagstar Bank is classified as a Loan Prospector user as it reported relying mainly on Loan Prospector during the period we analyze. Share sold to Freddie is $\frac{\text{\#Loans Sold to Freddie}}{\text{\#Loans Sold to Fannie or Freddie}}$. Portfolio share is the share of loans originated by the institution which were not sold in the the calendar year of origination. 10%, 5% and 1% significance levels are denoted by *, ** and ***. Sources: HMDA and authors' calculations.

TABLE 5
COUNTY STATISTICS BY EXPOSURE TO INITIAL LP USERS

	All	High	Low
Market share of early LP users by # of loans	2.9	4.5	1.3
	(2.9)	(3.4)	(0.5)
Share of population living in NOAA coastal county	36.9	41.0	32.7
	(48.3)	(49.2)	(47.0)
Per capita personal income (000s)	18.1	18.9	17.4
	(3.6)	(4.0)	(3.0)
Share of originations sold to either Fannie or Freddie	30.5	33.3	27.8
	(12.8)	(11.2)	(13.7)
# HMDA Respondents	194.5	211.2	177.8
	(106.7)	(114.6)	(95.4)
Market share of large HMDA respondents	28.1	30.3	25.8
	(9.8)	(9.3)	(9.8)
Ratio of owner (with mortgage) housing costs to income	28.1	27.9	28.2
	(4.0)	(4.1)	(3.9)
Share of persons 25+ with bachelors degree or higher	18.4	19.8	16.9
	(7.6)	(7.9)	(7.0)
Median value of owner-occupied housing (000s)	78.7	84.7	72.6
	(42.2)	(47.4)	(35.4)
Number of Observations	849	424	425

NOTES: This table shows county characteristics for all counties (Column 1) and for counties with above median (Column 2) and below median (Column 3) exposure to initial Loan Prospector users. All variables are measured in %, except income and the value of owner-occupied housing (measured in $000s) and the # of HMDA respondents, which is the number of institutions reporting HMDA data. The sample is restricted to counties in metropolitan areas with non-missing FHFA house price data. Sources: HMDA; 1990 decennial census; NOAA list of coastal counties; authors' calculations.

TABLE 6

HOW IS THE INITIAL LP SHARE RELATED TO COUNTY CHARACTERISTICS?

Dependent variable: County market share of early LP users in 1996.

	(1)	(2)
Share of population living in NOAA coastal county	0.23***	0.14***
	(0.06)	(0.04)
Log per capita personal income	-0.05	-0.10
	(0.07)	(0.06)
Share of originations sold to either Fannie or Freddie	0.08*	-0.00
	(0.05)	(0.04)
Log # HMDA Respondents	-0.02	0.00
	(0.05)	(0.04)
Market share of large HMDA respondents	0.46***	0.09
	(0.09)	(0.06)
Ratio of owner (with mortgage) housing costs to income	-0.19***	-0.17***
	(0.05)	(0.04)
Log median owner-occupied home value (1990)	-0.16**	-0.07
	(0.07)	(0.05)
Share of persons 25+ with bachelors degree or higher	0.16***	0.10**
	(0.06)	(0.05)
Market share of early LP or DU users by # of loans		0.63***
		(0.10)
Division FE	X	X
Number of Counties	849	849
Number of States	51	51
Within R-squared	0.19	0.44
Number of Observations	849	849

NOTES: This table shows estimated coefficients from: $EarlyLP_c = \alpha_d + \beta X_c + \epsilon_c$. $EarlyLP_c$ is the 1996 county market share of Loan Prospector users listed in Table 2 by number of HMDA loans (see Equation 1). All variables are normalized by dividing by the standard deviation. We include census division fixed effects. Standard errors are clustered by CBSA. The sample is restricted to counties in metropolitan areas with non-missing FHFA house price data. 10%, 5% and 1% significance levels are denoted by *, ** and ***. Sources: HMDA; 1990 decennial census; NOAA list of coastal counties; authors' calculations.

TABLE 7

EFFECT OF AUS ON PROCESSING TIME

Dependent variable: Time in days from application to closing/denial	(1) Originated	(2) Denied	(3) All
Early DU/LP User X Post	-1.868**	-5.014***	-2.153***
	(-2.14)	(-3.78)	(-2.66)
Lender × Income Quartile × Action FE	X	X	X
Number of Observations	2,738,647	469,260	3,207,907

NOTES: This table shows estimates of β from Equation 6. The sample includes denied applications and originated loans reported by the initial Desktop Underwriter users in Table 2, and a group of matched control lenders. The sample excludes applications for non-conventional loans. Column 1 is restricted to originations and Column 2 is restricted to applications that end in a denial. 10%, 5% and 1% significance levels are denoted by *, ** and ***. Standard errors are clustered by lender × income quartile. Sources: Confidential HMDA; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

TABLE 8

EFFECT OF LOAN PROSPECTOR ON COUNTY CREDIT AND HOUSE PRICES: 1993–1996

	House Price		High LTI		LTI	
	(1)	(2)	(3)	(4)	(5)	(6)
Early LP × Post	1.09***	0.95***	0.47***	0.51***	1.73***	1.91***
	(0.21)	(0.29)	(0.12)	(0.15)	(0.35)	(0.46)
Number of Counties	695	695	695	695	695	695
Number of States	51	51	51	51	51	51
Number of Observations	1,390	1,390	1,390	1,390	1,390	1,390

NOTES: Columns 1-4 show estimates of β from $Y_{c,t} = \delta_c + \gamma_{d,t} + \beta LP_c \text{Post}_t + \alpha X_c \text{Post}_t + \epsilon_{c,t}$. Columns 5-6 show estimates of β from $Y_{c,t} = \exp\left(\delta_c + \gamma_{d,t} + \beta LP_c \text{Post}_t + \alpha X_c \text{Post}_t\right) + \epsilon_{c,t}$. The dependent variable in Columns 1-2 is the log FHFA county house price index. The dependent variable in Columns 3-4 is the share of home purchase originations with a loan-to-income ratio above 2.5. The dependent variable in Columns 5-6 is the average LTI of home purchase originations (the top and bottom 1 per cent of income and loan size distributions each year are dropped before computing LTI). All specifications include county fixed effects and census division by year fixed effects and standard errors are clustered by CBSA. X_c include the following control variables: the combined market share of early LP and DU users (in columns 2, 4, and 6 only), coastal indicator, log median household income, log number of lenders, large lender market share, ratio of housing costs to income, log median property value, share with a bachelors degree or higher. The sample is restricted to counties in metropolitan areas with non-missing FHFA house price data and at least 250 purchase originations in 1993. 10%, 5% and 1% significance levels are denoted by *, ** and ***. Sources: HMDA; FHFA HPI; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

TABLE 9

PERCENTAGE OF 1993-2002 U.S. HOUSE PRICE GROWTH EXPLAINED BY LP&DU ADOPTION

Max. Horizon (years)	Year DU $\rightarrow$ LP rules: 1997		1998		1999	
	$\%_{1993-2002}$	$\hat{G}$	$\%_{1993-2002}$	$\hat{G}$	$\%_{1993-2002}$	$\hat{G}$
2	44	.134 (.048)	44	.134 (.048)	44	.134 (.048)
4	75	.216 (.058)	75	.216 (.058)	72	.207 (.058)
6	77	.221 (.061)	76	.22 (.06)	73	.211 (.06)
8	75	.216 (.061)	75	.215 (.06)	71	.206 (.06)

NOTES: This table shows the aggregate share of 1993-2002 U.S. house price growth explained by adoption of the GSEs' AUS ($\%_{1993-2002}$) and $\hat{G}$ from Equation 20 (bootstrapped standard errors in parentheses). The calculations are described in Section 6 and rely on two key inputs. The first is the aggregate share of loans underwritten using GSE AUS with rules comparable to the ones introduced by Freddie Mac with Loan Prospector. Public GSE data indicates that by early 1999 DU loans had a comparable DTI distribution to LP loans; however, as this is the earliest data available we do not know exactly when that shift occurred. Columns correspond to different assumptions regarding the year of the DU shift. Our estimated responses to LP adoption are also likely more credible closer to 1994. We therefore also show how setting the incremental response to zero at longer horizons affects the aggregate response. For aggregate effects, the short-run response is actually the most important. This is because the systems were not widely used before 1998, so responses at horizons longer than 4 years do not have much effect on national price growth to 2002.

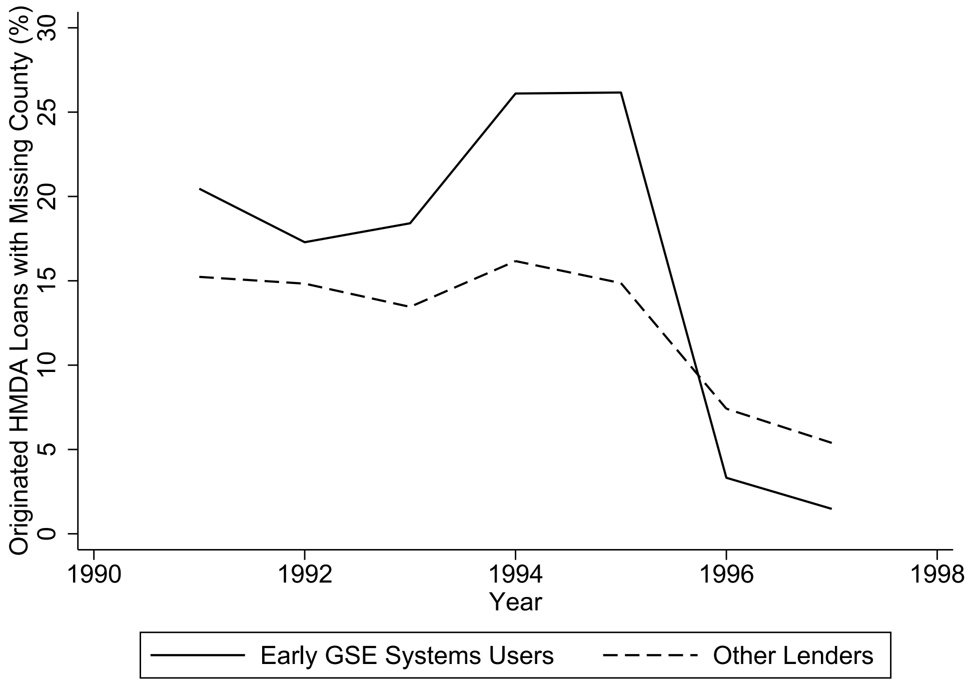
Internet Appendix

Financial Technology and the 1990s Housing Boom

Stephanie Johnson   Nitzan Tzur-Ilan

FIGURE B.1

SHARE OF HMDA ORIGINATIONS FOR WHICH THE PROPERTY LOCATION IS UNREPORTED

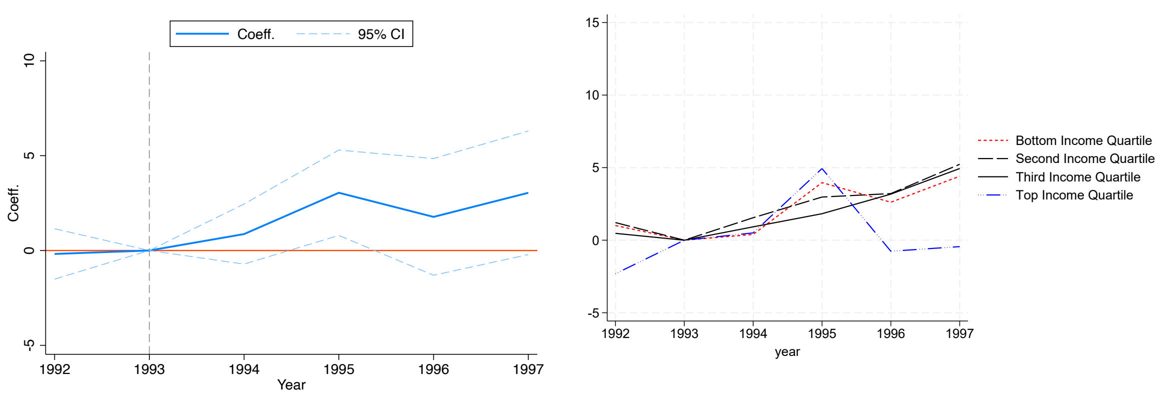


NOTES: This figure is constructed using HMDA originations from 1990–1997. Early GSE systems users are the lenders listed in Table 2. The increase in the availability of county information after 1995 reflects the implementation of new HMDA reporting requirements for property locations in 1996. Sources: HMDA and authors' calculations.

FIGURE B.2

EFFECT OF EARLY LOAN PROSPECTOR ADOPTION ON HIGH LOAN-TO-INCOME SHARE

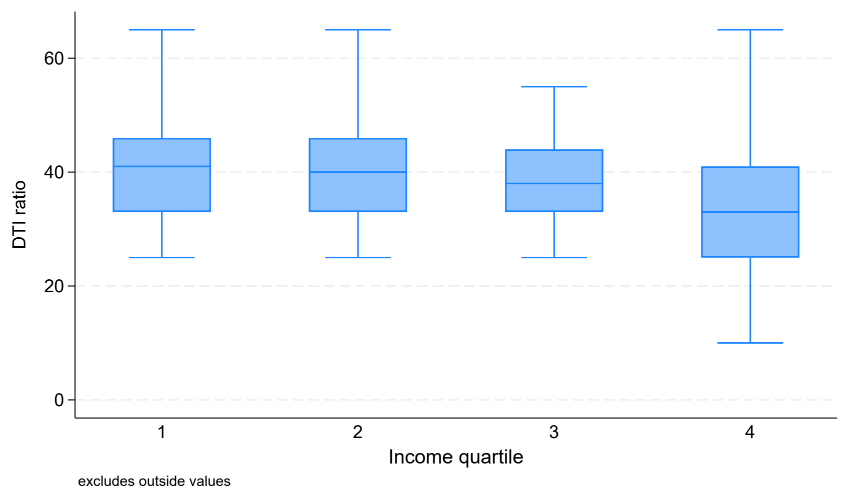
Panel A. Share LTI > 2.5 (pp) *Panel B. Share LTI > 2.5 (percentage points)*



NOTES: Figure B.2A plots estimates of $\{\beta_k\}$ from $HighLTI_i = \alpha_{l,n} + \gamma_{n,t} + \delta_{c,t} + \sum_{k \neq 1993} \mathbb{1}_{t=k} \beta_k LP_l + \epsilon_i$, where the dependent variable is an indicator equal to one for originations with a loan-to-income ratio (loan size divided by income) above 2.5 and zero otherwise. Figure B.2B plots the response separately for each income quartile.

FIGURE B.3

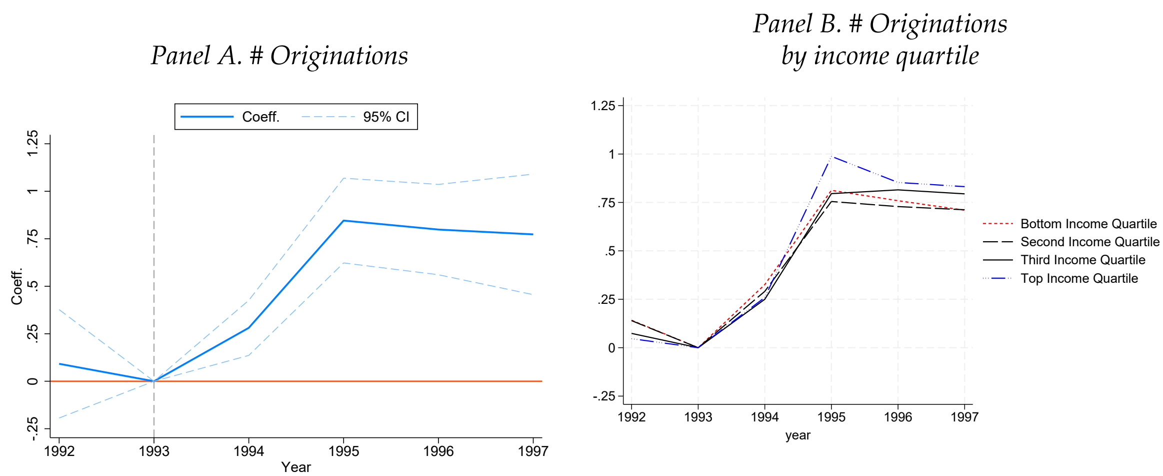
DEBT-TO-INCOME DISTRIBUTION BY INCOME QUARTILE



NOTES: This figure is constructed using 2018 HMDA home purchase originations. DTI ratios are top-coded at 60 per cent. Where DTI ratios are binned we assume the DTI is equal to the bin midpoint. DTI is reported by the lender and is the ratio of monthly mortgage payments, property insurance, property taxes, debt payments and certain other financial obligations to gross monthly income. Sources: HMDA and authors' calculations.

FIGURE B.4

EFFECT OF EARLY LOAN PROSPECTOR ADOPTION ON MORTGAGE ORIGINATION VOLUMES

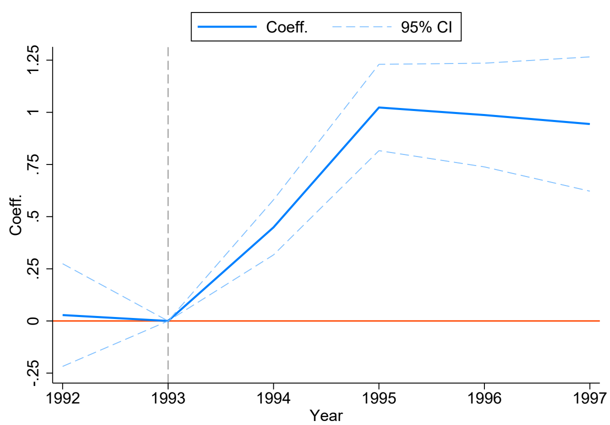


NOTES: Figure B.4A plots estimates of $\{\beta_k\}$ from Equation 5 To construct the dataset we first compute the aggregate number of originations for each lender by income quartile and year. Figure B.4B plots the response separately for each borrower income quartile. Standard errors are clustered by lender $\times$ income quartile.

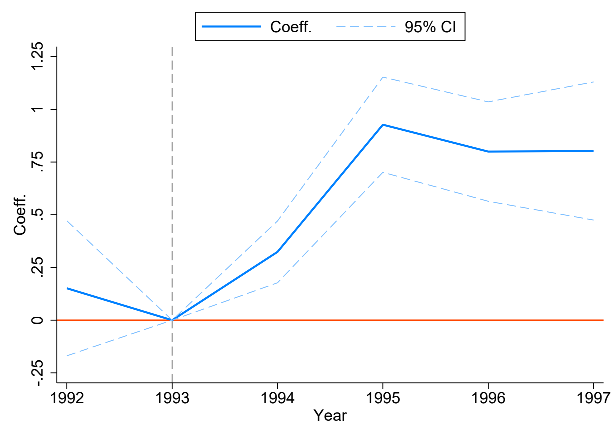
FIGURE B.5

EFFECT OF EARLY LOAN PROSPECTOR ADOPTION ON # LOANS BY LOAN PURPOSE

Panel A. # Purchase originations



Panel B. # Refinance originations

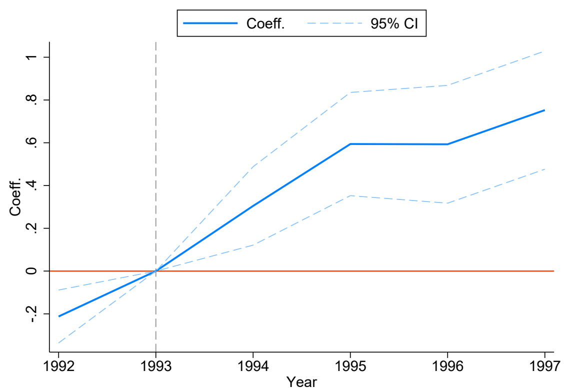


NOTES: This figure plots estimates of $\{\beta_k\}$ from Equation 5. The sample is restricted to home purchase originations in Figure B.5A and refinance originations in Figure B.5B. Standard errors are clustered by lender$\times$ income quartile. Sources: HMDA and authors' calculations.

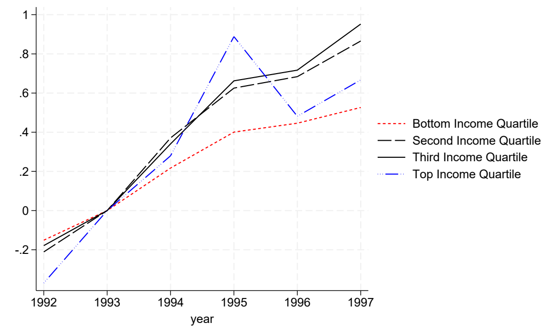
FIGURE B.6

ESTIMATED CREDIT RESPONSE WITHOUT LOCATION FIXED EFFECTS

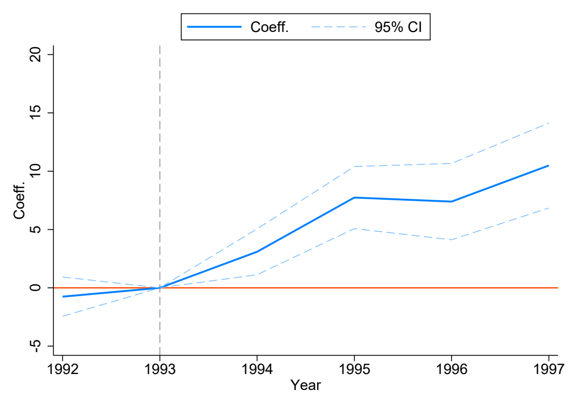
Panel A. Share LTI > 2.5 (Log Change)



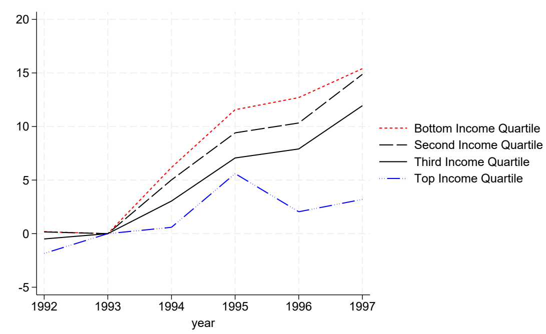
Panel B. Share LTI > 2.5 by income quartile (Log Change)



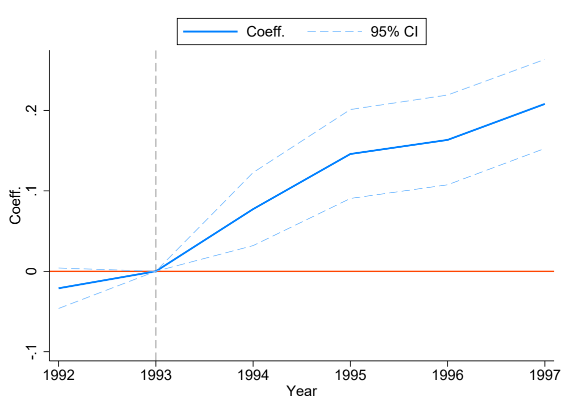
Panel C. Share LTI > 2.5 (pp)



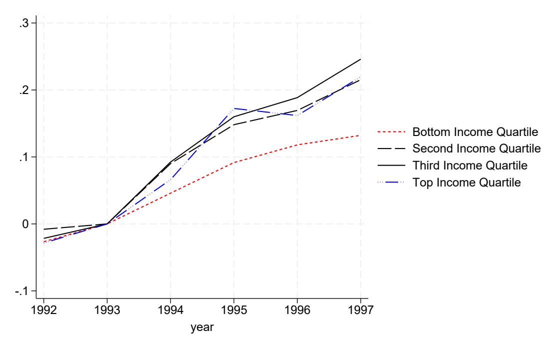
Panel D. Share LTI > 2.5 by income quartile (pp)



Panel E. LTI (Log Change)



Panel F. LTI by income quartile (Log Change)



NOTES: Refer to the notes to Figure 2. These figures are analogous but do not include location fixed effects (and the sample is therefore expanded to include loans and applications for which the property location was not provided). Sources: HMDA and authors' calculations.

FIGURE B.7

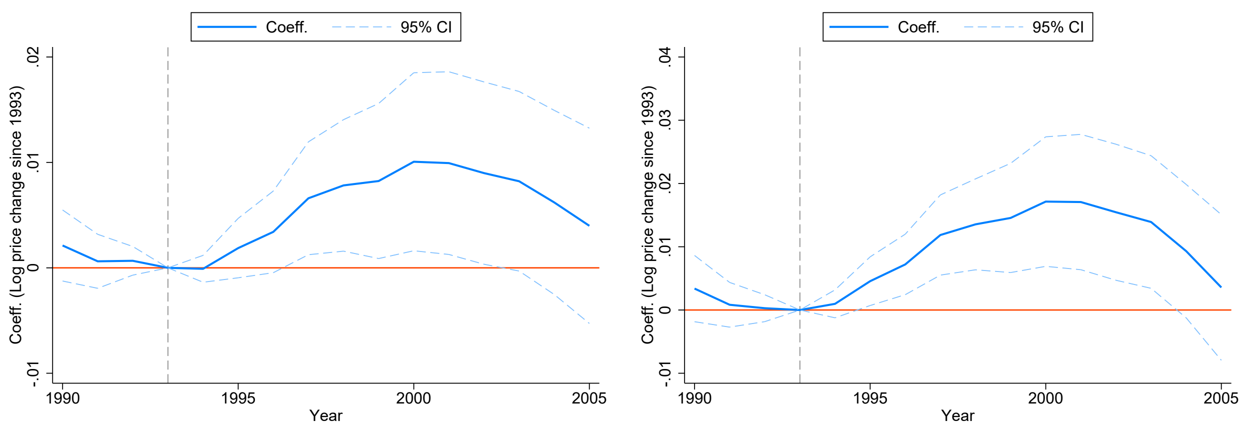
RANGE OF CREDIT ESTIMATES WHEN DROPPING LENDERS ONE AT A TIME

NOTES: Refer to the notes to Figure 2. We re-estimate the responses in Figure 2 with one lender dropped each time, and plot the range of estimated coefficients. Sources: HMDA and authors' calculations.

FIGURE B.8

RESPONSE OF HOUSE PRICES TO LOAN PROSPECTOR ADOPTION (1993 EXPOSURE)

Panel A. Relative to all lenders *Panel B. Relative to initial DU users*

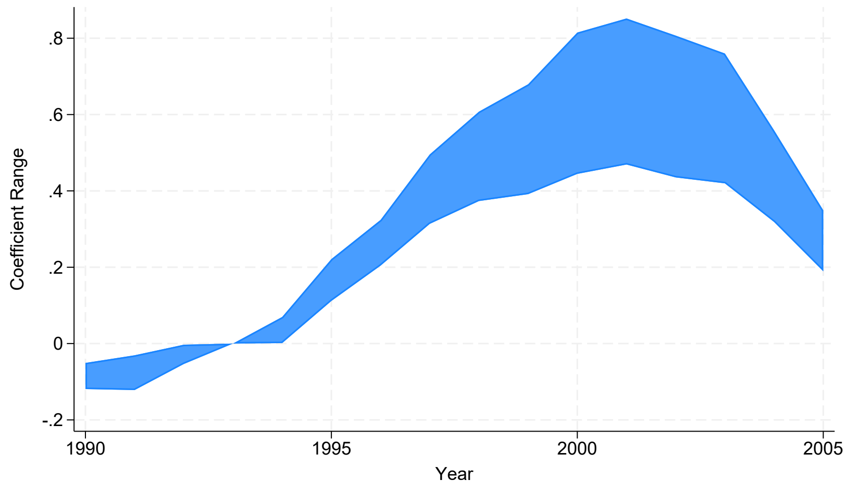


NOTES: Panel This figure plots estimates of $\{\beta_k\}$ from Equation 7 using an alternative exposure measure computed using 1993 HMDA data ($EarlyLP_{c,1993}$). Figure B.8B also conditions on $EarlyAUS_{c,1993}$ interacted with year dummies. See the notes to Figure 4 for additional details. Sources: FHFA HPI; HMDA; 1990 decennial census; NOAA list of coastal counties; BEA; and authors' calculations.

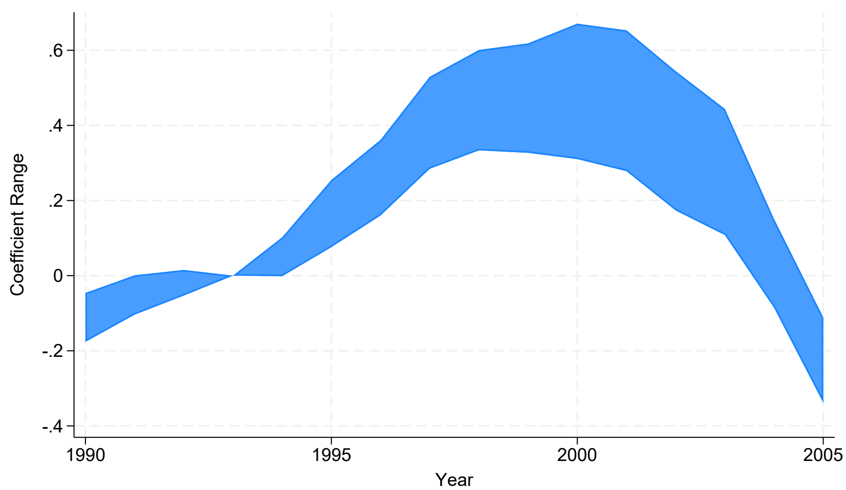
FIGURE B.9

RANGE OF HOUSE PRICE ESTIMATES WHEN DROPPING LENDERS ONE AT A TIME

Panel A. Relative to all lenders



Panel B. Relative to initial DU users

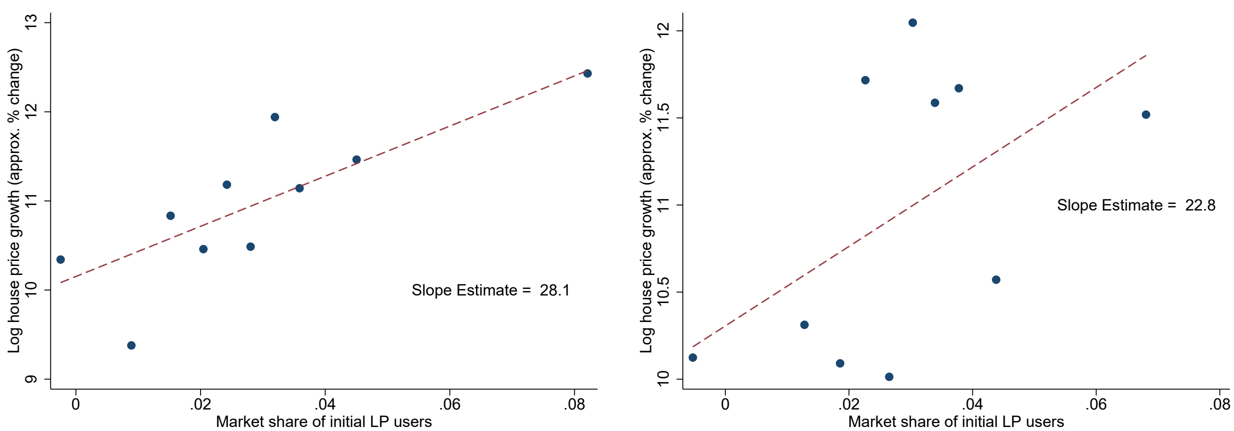


NOTES: This figure is constructed by re-estimating the coefficients reported in Equation 9 with one lender dropped each time before computing the exposure measure. Figure B.9B also conditions on $ShareLPorDU_c$ interacted with year dummies. Sources: FHFA HPI; HMDA; 1990 decennial census; BEA; NOAA list of coastal counties; and authors' calculations.

FIGURE B.10

RELATIONSHIP BETWEEN EXPOSURE AND 1993-1996 HOUSE PRICE GROWTH

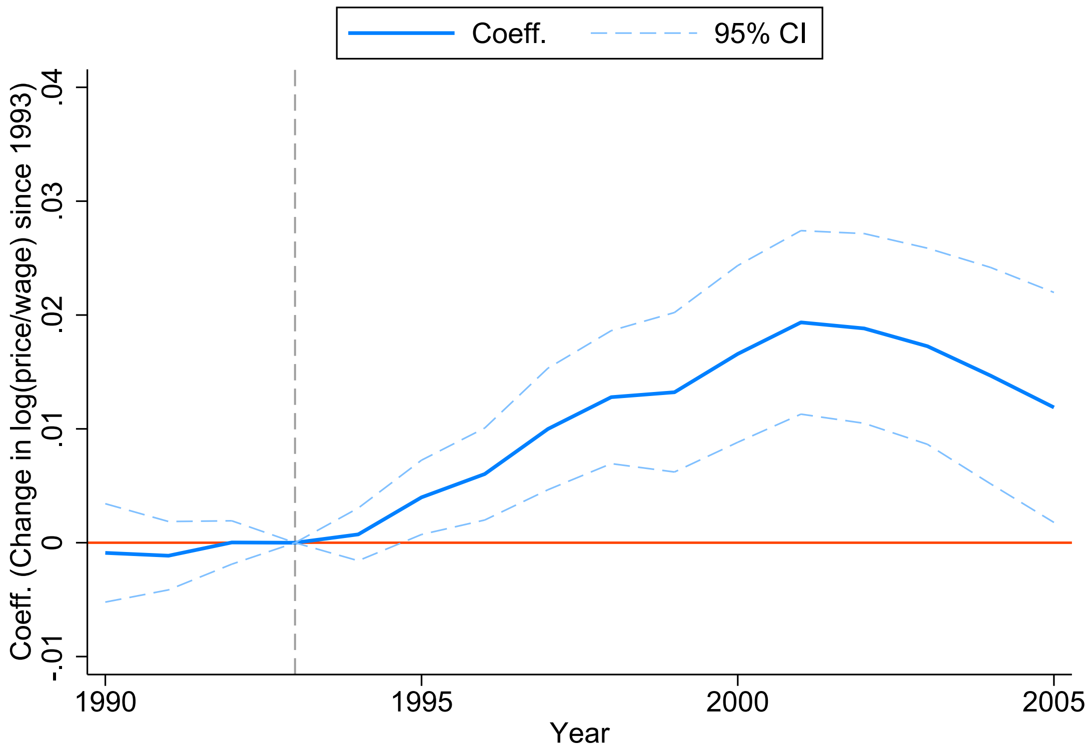
Panel A. Relative to all other lenders *Panel B. Relative to initial DU users*



NOTES: These binned scatter plots show the county log house price change from 1993-1996 by the county market share of initial Loan Prospector users. Both plots are conditional on the following county variables: county level controls (coastal indicator, log personal income per capita, share of originations sold to either Fannie or Freddie, log number of lenders, large lender market share, ratio of housing costs to income, log median property value, share with a bachelors degree or higher) and census division fixed effects. Figure B.10B is also conditional on the combined market share of initial LP and DU users. Sources: FHFA HPI; HMDA; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

FIGURE B.11

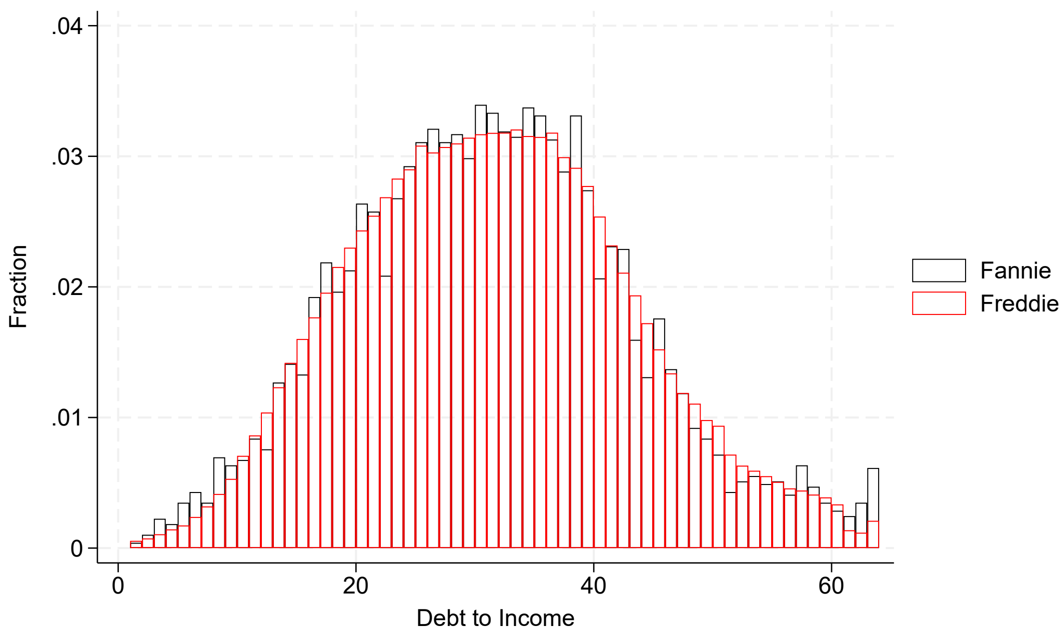
CUMULATIVE HOUSE PRICE RELATIVE TO PER CAPITA WAGE & SALARY GROWTH



NOTES: Figure B.11 plots estimates of $\{\beta_k\}$ from: $log(\frac{Price_{c,t}}{Wage_{c,t}}) = \delta_c + \gamma_{d,t} + \sum_{\substack{t=1990 \\ k \neq 1993}}^{2005} \mathbb{1}_{t=k} \left(\beta_k \frac{EarlyLP_c}{SD(EarlyLP_c)} + \alpha_k X_c \right) + \epsilon_{c,t}$. It conditions on the following county variables interacted with year dummies: coastal indicator, log personal income per capita, the share of originations sold to either Fannie or Freddie, log number of lenders, large lender market share, the ratio of housing costs to income, log median property value, share with a bachelors degree or higher. Coefficients are interpreted as cumulative log price changes relative to 1993. Standard errors are clustered by CBSA. The sample is restricted to counties in metropolitan areas with non-missing house price data. Sources: FHFA HPI; HMDA 1990 decennial census; NOAA list of coastal counties; BEA; and authors' calculations.

FIGURE B.12

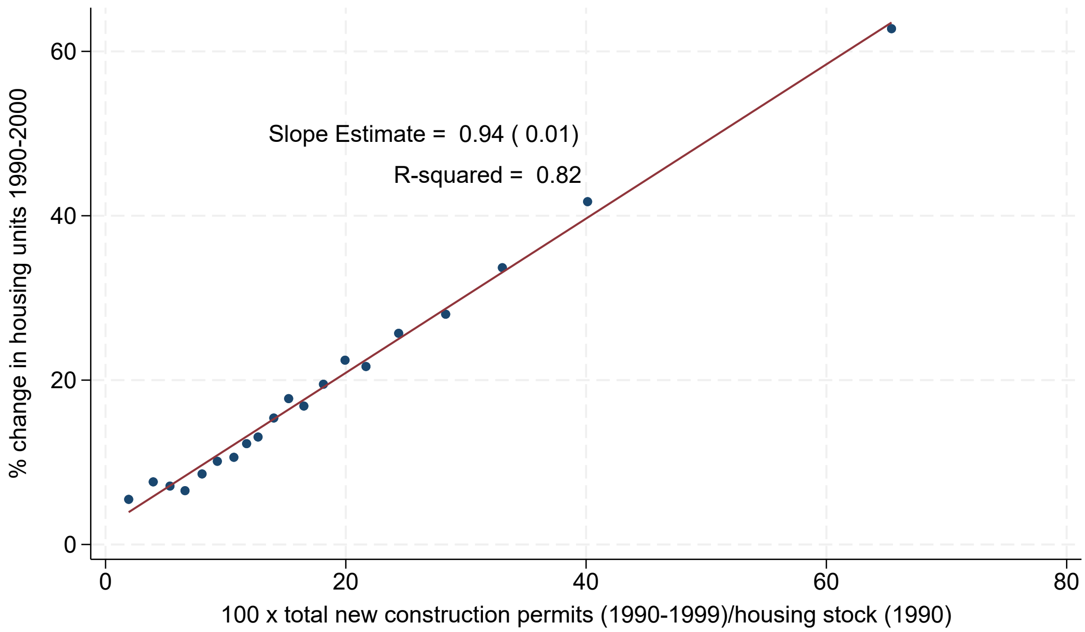
DTI DISTRIBUTION OF LOANS IN PUBLIC GSE DATA ORIGINATED BETWEEN JAN AND JUN 1999



NOTES: Figure B.12 plots the distribution of the back-end debt-to-income ratio using Fannie Mae's Single Family Loan Performance Dataset and Freddie Mac's Loan Level Dataset. We also include loans that were excluded from the originally released datasets to obtain more comprehensive coverage. We also drop loans sold by Norwest due to some unique characteristics of the distribution (Norwest reached an agreement to exclusively sell to Freddie around this time period in exchange for using an alternative underwriting system instead of LP).

FIGURE B.13

USING THE BUILDING PERMITS SURVEY TO IMPUTE HOUSING UNITS



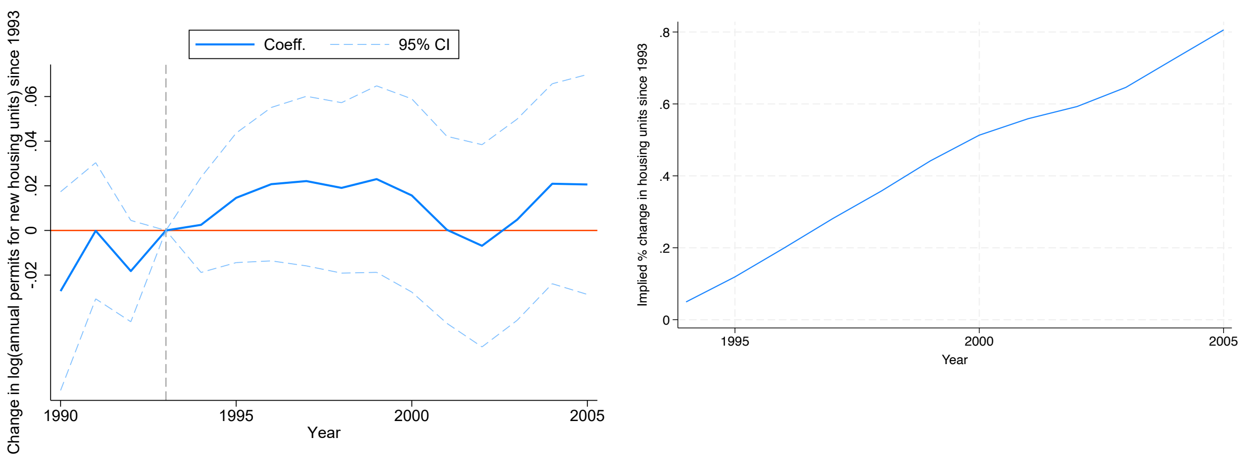
NOTES: Figure B.13 shows the relationship between actual and imputed growth in housing units from the 1990 to 2000 censuses. The vertical axis shows the actual percentage change in the number of housing units in a county. The horizontal axis shows the imputed growth as measured by total new construction permits in the BPS from 1990 to 1999.

FIGURE B.14

HOUSING SUPPLY RESPONSE MEASURED USING ANNUAL PERMITS ISSUED FOR NEW HOUSING UNITS

Panel A. Cumulative log change in annual new construction permits

Panel B. Cumulative % change in total housing units



NOTES: Figure B.14A plots estimated coefficents from $\log(Permits_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{t=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{t=k}\left(\beta_k \frac{EarlyLP_c}{SD(EarlyLP_c)} + \alpha_k X_c\right) + \epsilon_{c,t}$. Although the estimates suggest a statistically significant increase in permitted new units, the magnitude is small. Figure B.14B combines the estimates from Figure B.14A with 1990 data on the total county housing stock. The cumulative increase in housing stock from 1993 to 2003 is 0.65%. This implies a 10-year supply elasticity of 0.9.

TABLE B.1

CORRELATION BETWEEN AUS USAGE AND PROCESSING TIME

Dependent variable: Days from application to closing/denial.			
	(1)	(2)	(3)
	Originated	Denied	All
AUS Used	-2.910***	11.25***	4.319***
	(-92.16)	(116.80)	(148.43)
Ln(Loan Amount)	2.237***	2.533***	2.215***
	(144.75)	(46.31)	(141.65)
Ln(Income)	0.0472**	2.723***	2.083***
	(2.55)	(43.63)	(114.27)
Number of Observations	5,648,571	871,779	6,520,350

NOTES: This table shows estimates of β from: $Time_i = \gamma_{l,n} + \gamma_{g(l),t} + \beta AUSUsed_i + \alpha X_i + \epsilon_i$, where $AUSUsed_i$ is an indicator equal to one if an automated underwriting system was used and zero otherwise. The sample in column 1 is 2018-2019 originations, column 2 shows estimates for applications that are ultimately denied, and column 3 shows the relationship for all denied applications and originated loans. 10%, 5% and 1% significance levels are denoted by *, ** and ***. Sources: Confidential HMDA and authors' calculations.