Financial Technology and the 1990s Housing Boom *

Stephanie Johnson† Nitzan Tzur-Ilan ‡

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Abstract

The 1990s rollout of mortgage automated underwriting systems allowed for complex underwriting rules, cut processing time, and increased house prices. By comparing early systems with different characteristics, we separately estimate the effect of automation and the effect of new lending standards. 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 the share of lending at high loan-to-income ratios by around 30 per cent. Using exposure to initial adopters of Fannie Mae's Desktop Underwriter system (which initially did not apply new lending rules) we show that automation reduces loan processing time by up to one week but does not have a significant effect on house prices. House prices only grew differentially in these locations after Desktop Underwriter also started to apply new underwriting rules. Usage of both GSEs' systems accelerated during the late 1990s refinancing boom, dramatically changing the underwriting rules U.S. lenders used. Applying our estimated price response to later adopters, we suggest that the rollout of new lending standards with the GSEs' systems can explain a large share of U.S. house price growth between 1993 and 2002.

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†Jones Graduate School of Business, Rice University, 6100 Main Street, Houston, TX 77005. E-mail: stephanie.g.johnson@rice.edu.

‡Federal Reserve Bank of Dallas, 2200 N Pearl St, Dallas, TX 75201. E-mail: nitzan.tzurilan@dal.frb.org.

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 almost exclusively 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.[1]

Our paper is one of the first to explore the effect of credit conditions on house prices in the mid 1990s. As well as reducing processing time, automation 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]

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

[1]The empirical literature mostly focuses on securitization and the originate-to-distribute model as an explanation for the relaxation of credit conditions after 2002 (Keys, Seru and Vig (2012); Nadauld and Sherlund (2013); Rajan, Seru and Vig (2015); Griffin and Maturana (2016); Mian and Sufi (2022)). However, this channel is unlikely to explain a large part of national price growth in the late 1990s.

[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 do not claim that the rollout of AUS is the only explanation for house price growth during this period, but we think it is at least as important as branching regulation, if not more so. The relaxation of bank branching restrictions 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.

over two thirds of the change in house prices from 1993 to 2002. In contrast, automation reduced processing time by up to a week, but 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.

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 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 HMDA data, we find that lenders increased high loan-to-income (LTI) lending by around 30 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 Black Knight McDash mortgage servicing data (which does not identify the

[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.

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]

These estimates difference out effects of automation and focus on the shift to statistical rules. Next, we measure the effect of automation on processing time by comparing initial Desktop Underwriter adopters with lenders who were not initial adopters of either system. Because early versions of Desktop Underwriter continued to apply Fannie's manual underwriting rules, this allows us to study the effect of automation on processing time without a change in lending standards. We match initial AUS adopters with other HMDA lenders who had a similar business model in 1993. We find that processing time starts to decline for initial adopters coinciding with the 1994 pilot. Overall, AUS reduces processing time by about one week, with similar effects conditional on denial and origination.

Finally, we estimate the effect on house prices. We find that a one standard deviation (3.6 percentage point) increase in the market share of early Loan Prospector adopters leads to an additional 1 percentage point 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 23 per cent, or over two thirds 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.

Related Literature 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 (Adelino, Schoar and Severino (2016); Adelino, Schoar and Severino (2012); Di Maggio and Kermani (2017); Favara and Imbs (2015); Favilukis, Lud-

[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).

vigson and Van Nieuwerburgh (2017); Foote, Loewenstein and Willen (2020); Greenwald (2018); Greenwald and Guren (2021); Griffin, Kruger and Maturana (2021); Justiniano, Primiceri and Tambalotti (2019); Kaplan et al. (2020); Landvoigt, Piazzesi and Schneider (2015); Mian and Sufi (2009)). Second, we contribute to a growing literature on fintech and the use of automated underwriting (Fuster, Plosser, Schnabl and Vickery (2019); Buchak, Matvos, Piskorski and Seru (2018); Foote, Loewenstein and Willen (2019); Jansen, Nguyen and Shams (Forthcoming); Wei and Zhao (2022)). We highlight the fact that automated underwriting in mortgage markets is far from a recent development, and are the first to provide direct quasi-experimental evidence that the rollout of AUS in the 1990s contributed to the subsequent national housing boom.

Our paper supports the idea that the boom was triggered by a change in lending standards, though expectations may still have played an important role in amplifying the response.[5] We identify a specific change in lending standards that is both large and highly correlated across lenders and locations: new rules applied through automated underwriting systems. Existing explanations based on lending standards tend to focus on a credit expansion specifically to low income borrowers. In contrast, the expansion we focus on is likely to have had broader effects across the income distribution for two reasons. First, we show that debt-to-income limits were initially expanded more for borrowers who also made substantial down payments. Second, we note that the DTI distribution is similar across the lower three income quartiles (Figure A.1).[6]

Our empirical setting predates much of the reduced-form work examining the housing boom. For example, Adelino et al. (2016); Foote et al. (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. Adoption of automated underwriting systems 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. In addition, Favara and Imbs (2015) show that bank branching deregulation affected only portfolio

[5]We also do not take a stand on the causes of house price growth after 2002 – a period that is the focus of a large amount of work by other authors. Locations that were more exposed to the initial Loan Prospector adopters experienced an earlier housing boom rather than a larger boom overall. However, we cannot rule out positive long-run effects given the eventual similarity of Loan Prospector and Desktop Underwriter, as well as widespread adoption of the systems by lenders (both of which should bias our estimates towards zero at long horizons).

[6]This observation is based on recent data. We cannot construct similar statistics prior to 2018 because DTI was not included in the HMDA dataset.

loan originations. The GSEs' systems were widely used as a general underwriting tool, both for loans intended for sale (to the GSEs and others) and for portfolio loans.

Foote et al. (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. In contrast to our conclusions, Foote et al. (2019) propose that these developments did not directly affect house prices, pointing to the absence of stronger relative house price growth in low-income zip codes during 1990s. In this paper we directly estimate large effects of AUS adoption on house prices using a difference-in-differences approach leveraging gradual adoption of the systems (which were not widely used until well after their release date). We also show that the effects of AUS adoption on credit are not limited to low income borrowers.

In contrast to much of the empirical literature, papers taking a structural approach typically model the effect of changes occurring in 2000 or earlier (Favilukis et al. (2017); Greenwald (2018); Greenwald and Guren (2021); Justiniano et al. (2019); Kaplan et al. (2020)). 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. Our empirical strategy focusing on early AUS adopters provides direct evidence that this shift had a large effect on house prices.

Ferreira and Gyourko (2011) note that while some markets experienced a housing boom starting 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 the adoption of non-traditional mortgage products. In this paper we show that financial innovation, in this case statistical lending standards, also seems to be important for the early boom.

Our paper also relates to recent work studying the effect of fintech on the mortgage market. Fuster et al. (2019) and Buchak et al. (2018) study the post-crisis period and emphasize the convenience of fintech. Fuster et al. (2019) document the processing advantages offered by fully online applications. Here, we study the effect of automated underwriting adoption on processing time. This is a related but distinct question as automated underwriting is also used by lenders who do not offer fully online applications. Our historical focus on initial adopters of AUS in the mid 1990s offers substantial identification advantages. While more recent datasets contain information about AUS usage at the loan level, the present widespread use of AUS means that there is also likely substantial bias introduced by the choice of when to use these systems.

We find that AUS usage reduces processing time by about a week, which is broadly comparable to the reduction in processing time associated with the fully online application process offered by fintech lenders (Fuster et al., 2019). Though processing advantages may have been important for AUS adoption and the rollout of statistical underwriting standards, we find that they do not directly affect house prices.

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, 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 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

[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 an input into Loan Prospectors' recommendation, 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).

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 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 Har-

[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).

[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.

ney (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 A.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 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

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

[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.

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 A.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).

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 MSAs. The dataset includes mortgage originations and loan purchases, as well as applications that did not lead to an origination. We also use confidential supervisory data collected under the HMDA to construct a measure of processing time from application dates and closing/decision dates.

We supplement the HMDA data with Black Knight McDash mortgage servicing data – a loan-level dataset with information obtained from a number of large servicers. McDash covers a variety of loan types, including portfolio loans, agency loans, nonconventional 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 house price indices to study the effect on house prices.

3.1 Lender statistics

Tables 1 and 2 list initial users of Loan Prospector or Desktop Underwriter. These lenders were already using the systems at the time of public release in 1995. We manually identify HMDA IDs associated with theses lenders based on name and location. Both groups contain a mixture of large and mid-sized lenders, as well as thrifts, commercial banks and independent mortgage banks. Because DU initially applied Fannie's manual rules, we can use initial users of DU as a control group to quantify the effect of the 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 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.

Comparison of initial LP and initial DU users

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).[14] 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.

Comparison of initial DU users and matched lenders not using GSEs' AUS

When estimating effects on processing time, we compare initial DU users with a sam-

[14]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).

ple of matched control lenders. Table A.2 shows a linear probability model where the dependent variable is an indicator equal to 1 for initial DU users (the 'treatment' group) and 0 for the group of matched control lenders (there are three for each 'treated' lender). The matching procedure targets the portfolio share, the refinance share and the share of loans that were purchased rather than originated. Correlations are generally insignificant, even for unmatched variables. The main difference between the lenders is that those participating in the DU pilot sold a larger share of loans directly to Fannie or Freddie, suggesting that they had closer direct ties to the GSEs. While control lenders sell a similar share of loans overall, if not more, non-GSE buyers account for a larger share of sales (some of these loans may ultimately have been sold on to the GSEs but it is not possible to determine that using HMDA).

3.2 County statistics and exposure measure

In Section 5.3, we use variation in county exposure to initial adopters of Loan Prospector to study the effect on county house prices:

$$EarlyLP_c = \frac{\text{\# Loans reported in county } c \text{ by lenders in Table 1}}{\text{\# Loans reported in county } c \text{ by all HMDA reporters}} \tag{1}$$

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

$$EarlyLPorDU_c = \frac{\text{\# Loans reported in county } c \text{ by lenders in Table 1 or Table 2}}{\text{\# Loans reported in county } c \text{ by all HMDA reporters}} \tag{2}$$

Conditioning on $EarlyLPorDU_c$ 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, several lenders in Tables 1 and 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.[15] From 1996 onward, banks or thrifts

[15]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.

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 A.2, location reporting improved considerably.[16]

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

We further show in Section 5.3 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.

[16]Figure A.2 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). Given location reporting requirements prior to 1996, this could reflect an increase in lending further from the lenders' branch locations.

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 Empirical approach

Next we lay out our empirical approach in more detail.

4.1 Credit outcomes

In Section 5.1 we quantify how moving to statistical lending standards affects credit outcomes, holding automation fixed. For this analysis we compare initial LP users with initial DU users over the period 1992-1997. As we discuss in Section 2.2, the switch to statistical standards relaxed debt-to-income ratio requirements. However, DTI is not available in the HMDA data, which provide the best coverage for this period and identify the lender. We consider three HMDA credit outcomes: (1) the total number of loans; (2) the share of loans with a loan-to-income ratio above 2.5; and (3) the average loan-to-income ratio. We also report effects on credit denial rates in the appendix.

We first compute the number of loans reported by lender l in income quartile n in year t and estimate the approximate percentage change in the number of loans using Poisson regression:

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

where LP_l is an indicator equal to one for early LP users (lenders listed in Table 1) and zero for early DU users (lenders listed in Table 2). β_k is interpreted as the log change in number of loans between the base year (1993) and year k.[17]

Next we look at effects on high LTI lending. We define $HighLTI_i$ equal to one if the loan-to-income ratio exceeds 2.5 and zero otherwise. We estimate the percentage point

[17]Unlike linear regression where the dependent variable is the log of the outcome of interest, Poisson regression 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)). Although usually used for count data, it can also be used for analyzing non-negative continuous outcomes.

response using a specification with county-year and income quartile-year fixed effects:

$$HighLTI_i = \alpha_{l,n} + \gamma_{n,t} + \delta_{c,t} + \sum_{k \neq 1993} \mathbb{1}_{t=k} \beta_k LP_l + \epsilon_i \tag{4}$$

and the approximate proportional response using:

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

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.[18] Figure A.3 shows the distribution of DTI ratios by LTI quartile and income. There is a clear positive relationship between DTI and LTI, but there is also considerable variation in DTI across households with lower LTIs.

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. Figure A.1 shows that the DTI distribution in recent HMDA data is very similar for households in the bottom

[18] 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 bought their home in the last 5 years.

two income quartiles, and high DTI borrowing spans the entire income distribution.

We are able to estimate effects on high DTI lending using McDash, but caution that it is a much smaller sample and does not identify the lender. Our analysis is therefore based on local exposure to each group of lenders rather than a direct comparison of loans made by each group of lenders. We use the following specification, where loan i is secured by a property in county c, in census division d:

$$HighDTI_i = \delta_c + \gamma_{d,t} + \sum_{k=1994}^{1997} \mathbb{1}_{t=k}\left(\beta_k EarlyLP_c + \alpha_{1,k} X_c + \alpha_{2,k} X_i\right) + \epsilon_i \tag{6}$$

$EarlyLP_c$ 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 on average and rapidly decreasing. 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 be interpreted as a hard cutoff.[19]

4.2 Processing time

In Section 5.2, we study the effect of AUS on mortgage processing time focusing on initial DU users, for whom lending standards did not initially change. We adopt a different empirical approach to quantify effects on processing time, as this requires comparing initial users of 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 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).[20]

[19] 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.

[20] 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.

As a robustness check, we also construct a set of control lenders for initial LP users and find similar effects on processing time. We estimate:

$$Time_i = \alpha_{l,n} + \gamma_{g(l),t} + \beta_0 DU_l + \beta_1 DU_l \cdot Post_t + \alpha_1 X_i + \alpha_2 X_i \cdot DU_l + \epsilon_i \qquad (7)$$

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. Lender group $g(l)$ includes lender l as well as the three matched control lenders. DU_l is an indicator equal to one for initial DU 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. Controls include the log loan amount, log income, and their interaction with DU_l.

4.3 House prices

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

$$\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{t=1990 \\ k \neq 1993}}^{2005} \mathbb{1}_{t=k} \left(\beta_k \frac{EarlyLP_c}{SD(EarlyLP_c)} + \alpha_k X_c \right) + \epsilon_{c,t} \qquad (8)$$

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.

4.4 Interpretation

All 'treatment' groups are constructed based on lenders who participated in the GSEs' pilot programs. That is, lenders who were already using the systems to some extent at the time of public release. However, we cannot quantify the percentage usage of the systems by initial users as AUS usage is not covered by mortgage datasets during this time period.

Trade publications indicate that several large initial adopters were quick to roll out the systems at scale. Lenders reported using the systems broadly, for non-conforming loans, portfolio loans and for loans originated through non-retail channels (LaMalfa (1996); LaMalfa (1997); LaMalfa (1998)). To the extent that early Loan Prospector users did not stick with their original choice of system, or did not roll out the system on a large scale, this should attenuate the responses we estimate relative to the full effect of the systems (though the information lenders gained about the system could still have changed their risk perceptions and affected their standards).

For lender outcomes 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.

5 Results

5.1 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 effects of automation alone. We find that initial LP adopters make more loans, lend more relative to income and deny fewer applications. Using 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.

Figure 2A shows the effect on mortgage originations, plotting estimates of $\{\beta_k\}$ from Equation 3. Initial LP adopters start to grow originations relative to initial DU adopters in 1994. The cumulative log change peaks at 0.865 in 1995, meaning the number of loans made by early Loan Prospector adopters was about 136 per cent higher in 1995 than 1993 (relative to the corresponding change for initial DU adopters). This 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. The response is similar across income quartiles (Figure 3A) and for purchase and refinance loans (Figure A.4).[21]

Next we look at effects on loan amount relative to borrower income. Figure 2B shows a 5 percentage point increase in the high LTI share of originations. Figure 2C shows an approximate 30 per cent increase in the high LTI share. The proportional response is similar across most of the income distribution, though low-income households tend to have larger loans relative to income and percentage point responses are therefore larger for this group (Figures 3B and 3C). Finally, Figure 2D shows approximate percentage effects on the average loan-to-income ratio. Average LTI increases gradually with a peak effect of about 12 per cent in 1997, and a similar proportional response across the income distribution in Figure 3D.

Overall, we find large positive effects on LTI. Depending on the outcome and specification, we sometimes find larger effects for lower income households. However, we find large positive effects on lending for the bottom 75 per cent of the income distribution across virtually all specifications, indicating that the shift to statistical lending standards did not just benefit low income borrowers.

Our main specifications include county-year fixed effects, which means we compare loans made by initial LP and DU users in the same county. This helps us rule out alternative narratives that predict higher borrowing relative to income in locations with more LP users. However, we repeat the analysis without conditioning on location because the location of the property is missing for a large share of HMDA loans prior to 1996. Missing location data is particularly problematic in light of poor coverage for some initial adopters (Figure A.2) and may introduce other sources of bias.

Note that we never use county fixed effects when the dependent variable is the number of originations (Equation 3) because changes in location reporting are likely to be particularly problematic for volumes. For other outcomes where we do condition on location in the main specification, we show in Figure A.6 that qualitatively similar results are obtained when expanding the sample to include loans with unknown location. Quantitatively, the responses are larger when we do not condition on location.

[21] Denial rates may also be informative about the extensive margin response. Figure A.5 shows that the mortgage denial probability declines by at least 2 percentage points with larger effects depending on the specification. However, we do not place a high weight on these results. HMDA denials may not be reported consistently across lenders, loan types and time. In addition, denial rates can be an inaccurate measure of lending standards when the risk of the applicant pool shifts at the same time. Controlling for the composition of the applicant pool is hard because HMDA does not contain information on credit score, LTV and DTI during our sample period. In Figure A.5 we drop cases with unusual denial patterns and include income quartile by year fixed effects to try to address these concerns.

This could partly reflect feedback effects from stronger house price growth to credit demand. County-year fixed effects likely absorb much of this response and push our credit estimates closer to the direct effect of LP adoption.

We also verify that the results are not driven by a single lender. Figure A.7 shows the range of estimated coefficients obtained by dropping each lender in turn. The responses are fairly robust across all variables.

To study effects on the debt-to-income ratio we supplement our analysis with McDash data. McDash also allows us to examine interactions with the loan-to-value ratio. While McDash does include additional underwriting variables, the dataset 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.[22] Given these limitations, we view the McDash analysis as providing suggestive support for our other estimates.

Figure 4A shows that a one standard deviation increase in the market share of initial LP users leads to a peak 1.4 percentage point increase 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. Including county controls interacted with year dummies has little effect on the size of the estimates. Figure 4B 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 around 1.8 percentage points. There is some suggestive evidence that this requirement was later relaxed, consistent with Freddie Mac increasing DTI limits for a broader set of borrowers.

5.2 Processing time response

Table 7 shows estimates of β_1 from Equation 7 for home purchase loans. The time from application to closing/denial declines by about 5 days for initial DU users relative to matched lenders. When we estimate Equation 7 separately for denied and originated

[22] We do not condition on credit score. 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. 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.

loans we find a processing time reduction of about $6\frac{1}{2}$ days in each case.[23]

This effect is a little 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). We note that the technology we consider is different from Fuster et al. (2019), who focus on lenders with a fully online application process, which is a more recent industry development. Given their recent setting it is also very likely that the 'non-Fintech' lenders in their sample use an AUS too. Taken together, our results suggest that the combined effect of automated underwriting and a fully online process could be a processing time reduction of as much as two weeks.

Our historical setting is particularly well-suited to 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. The problem with recent data is that AUS usage is widespread and likely subject to considerable selection bias. To illustrate this, we re-estimate Equation 7 with 2018-2019 HMDA data and replace DU_l with an indicator for whether an AUS was actually used to underwrite application i. Appendix Table A.3 shows that AUS usage is associated with a six day *increase* in processing time on average. Conditional on denial, processing time increases by over two weeks. Even conditional on origination, AUS usage is associated with a modest one day reduction in processing time.

5.3 House price response

Next we estimate the effect of AUS adoption of house prices. We start by plotting price growth since 1993 for counties with very high and very low exposure to Loan Prospector (Figure 5A). 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.

Next, we use Equation 8 to more formally estimate the effect of Loan Prospector on house prices. A one standard deviation increase in exposure to Loan Prospector raises prices by around 0.7 per cent in 1996 with a peak (cumulative) effect of around 1.8

[23]We find no significant effect on processing time for refinance applications for initial DU users. While we do find a significant $2\frac{1}{2}$ day reduction for initial LP users for refinance applications (relative to matched control lenders), this is almost entirely driven by faster denials. The limited effect for refinance applications 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.

per cent (Figure 5B). The house price response grows for several years after the original shock. Further relaxation in the rules applied by LP is consistent with the credit analysis and narrative evidence, though the magnitude is likely too large to be fully accounted for by this. Price momentum is another possible explanation, for example through feedback channels such as adaptive expectations. It is hard for us to test this without data on local price expectations, but it seems consistent with survey evidence relating experiences of recent price growth to expectations of future price growth (Armona, Fuster and Zafar (2019); Bailey, Cao, Kuchler and Stroebel (2018); Case, Shiller and Thompson (2012)).

Figure 5C further conditions on the county share of lenders who were either early DU or early LP adopters, $EarlyLPorDU_c$. This specification is more consistent with the approach in Section 5.1, where we compare loans made by initial LP adopters with loans made by initial DU adopters. However, conditioning on the combined share removes a lot of the variation in exposure and the estimates are less precise. Overall, both responses are of a similar magnitude. Neither specification exhibits a significant pre-trend, which helps to address concerns about correlations with other county-level factors driving house price growth.

We note that our estimates of the house price response are more informative at shorter horizons. Eventually Desktop Underwriter incorporated more relaxed lending standards and both systems became more widely used. These developments would lead to lending standards in the 'control' group converging to lending standards in the 'treatment' group over time. Consistent with this story, the difference in house prices across these areas declines during the 2000s. That is, locations exposed to early Loan Prospector users experienced an earlier housing boom, but other locations catch up. Given the usage data in Table A.1, we feel that our estimates are most useful prior to 1998, when the systems started to become widespread.

To verify that the house price response to Loan Prospector adoption is driven by the accompanying switch to statistically-informed lending standards, we also estimate the house price response following adoption of Desktop Underwriter, which initially only automated Fannie Mae's existing manual underwriting rules. Figure 6A plots estimates of $\{\beta_k\}$ from:

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

Figure 6B also conditions on the combined market share of initial DU users and matched control lenders. Both figures show analogous estimates for initial LP users 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:

$$\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{k=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{t=k}\left(\beta_k EarlyLP_c + \alpha_k X_c\right) + \epsilon_{c,t} \tag{10}$$

Exposure to initial DU users leads to an insignificant increase in house prices, much 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

Figure A.8 shows estimates of $\{\beta_k\}$ from Equation 8 when computing exposure using 1993 data. The 1993 measure effectively excludes activity by depository institutions in locations where they did not have physical branches. The results are nonetheless fairly similar. We also test whether the house price results are driven by a single lender. We construct alternative measures of $EarlyLP_c$ and $EarlyLPorDU_c$, dropping each lender sequentially. Figure A.9 shows that dropping individual lenders does not qualitatively change the main result. Finally, Figure A.10 plots the relationship between 1993-1996 house price growth and the county exposure measure conditional on a number of county characteristics.

Magnitude

To compute the elasticity of house prices to credit, we also 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.[24] Average LTI in-

[24]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 A.2). In 1996 HMDA location reporting rules were tightened and missing location shares declined.

creases by 1.7-1.9 per cent depending on the specification. The high LTI share increases by 0.6-0.7 percentage points. 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).

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 A.1 to compute a cumulative aggregate log price response from 1993 to 2002:

$$\hat{g} = \sum_{k=1994}^{2002} s_{1994+(2002-k)} \hat{\beta}_k \tag{11}$$

where $\{\hat{\beta}_k\}$ are the estimated coefficients from Equation 10 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 A.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.

We also assume that Desktop Underwriter applied similar rules to Loan Prospector starting in 1998, and that the response estimated for early LP users can also be applied to DU users after this point. That is, we think of 'adoption' as the adoption of statistical underwriting standards for this exercise. We set the adoption rate to zero for DU prior to 1998, which generates a large jump in our adoption measure in 1998 equal to the cumulative adoption of DU up until that point. Although the precise timing of these changes to DU is unclear, by 1999 public GSE loan-level data suggest the two systems were indeed very similar. Equation 11 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 be interpreted with these caveats in mind.

We compute a cumulative log price response from 1993 to 2002 of 0.21 when comparing early LP users with all other lenders. The bootstrapped standard error is 0.034 and the percentage price response is 23.2%. When conditioning on on the combined share of early LP and DU users the effect is 23.8%. This is a substantial effect, and means that adoption of statistical underwriting standards accounts for more than two-thirds of national price growth over this period.[25]

6 Conclusion

We use the 1990s rollout of the GSEs' automated underwriting systems to study 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 at least two-thirds of aggregate U.S. price growth in the early stages of the 2000s housing boom.

[25] We compute the percentage price response as $100 \times (e^{\hat{g}-\frac{1}{2}\hat{\sigma}_{\hat{g}}^2} - 1) = 100 \times (e^{0.20952-\frac{1}{2}(0.03378)^2} - 1)$ as recommended by Kennedy (1981). In this case adjusting for the variance of $\hat{g}$ makes very little difference.

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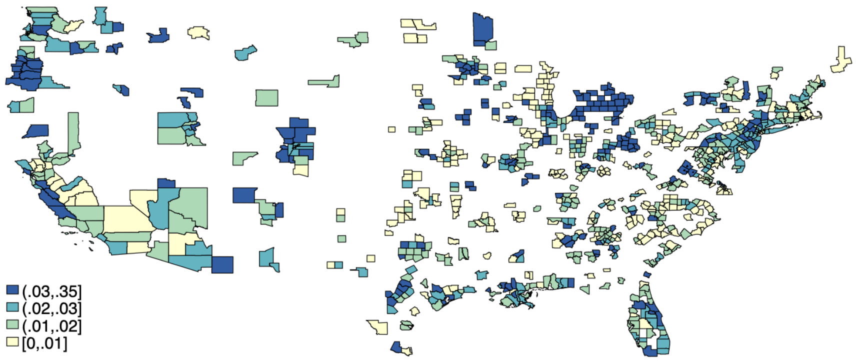
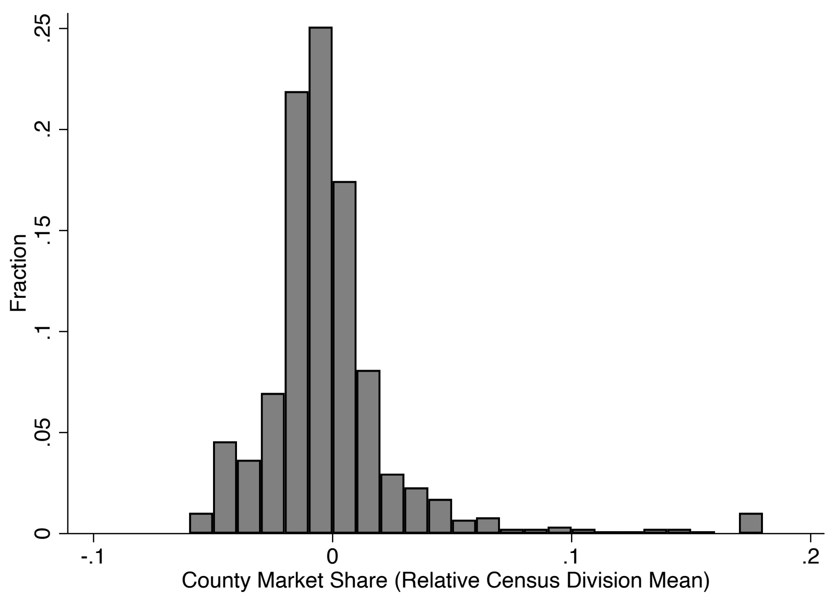
FIGURE 1

MARKET SHARE OF INITIAL LOAN PROSPECTOR USERS

Panel A.



Panel B.

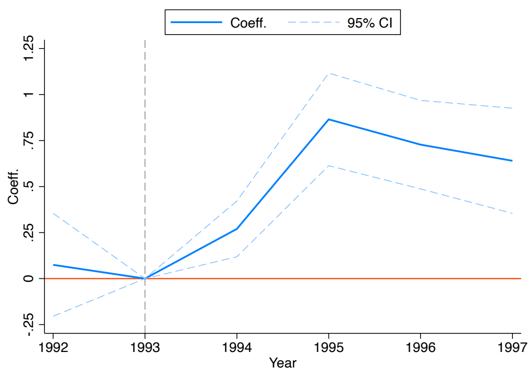


NOTES: Panel 1A maps the exposure measure: $EarlyLP_c = \frac{\text{\# Loans reported in county } c \text{ by lenders in Table 1}}{\text{\# Loans reported in county } c \text{ by all HMDA reporters}}$. Market shares are computed using 1996 HMDA originations and purchases and include both purchase and 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.

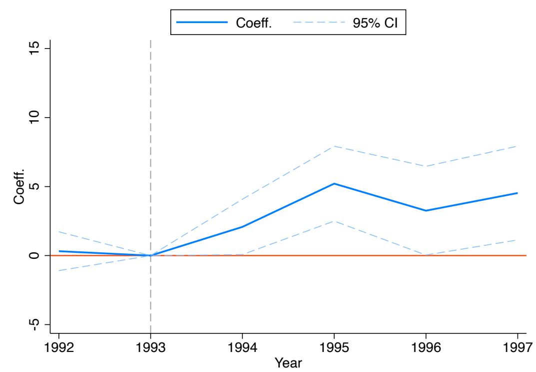
FIGURE 2

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

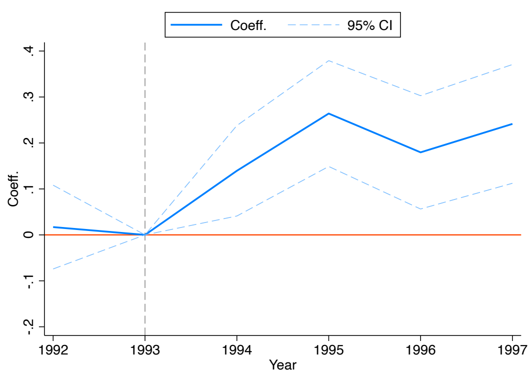
Panel A. # Originations



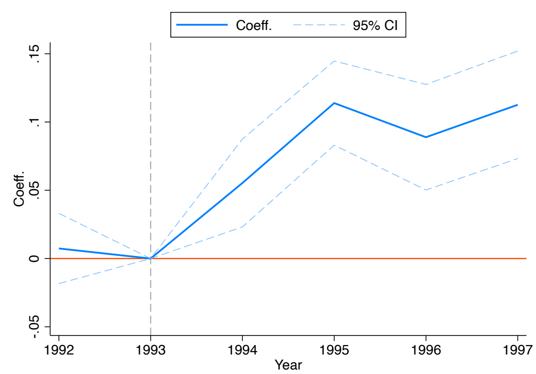
Panel B. Share LTI > 2.5 (pp)



Panel C. Share LTI > 2.5 (log change)



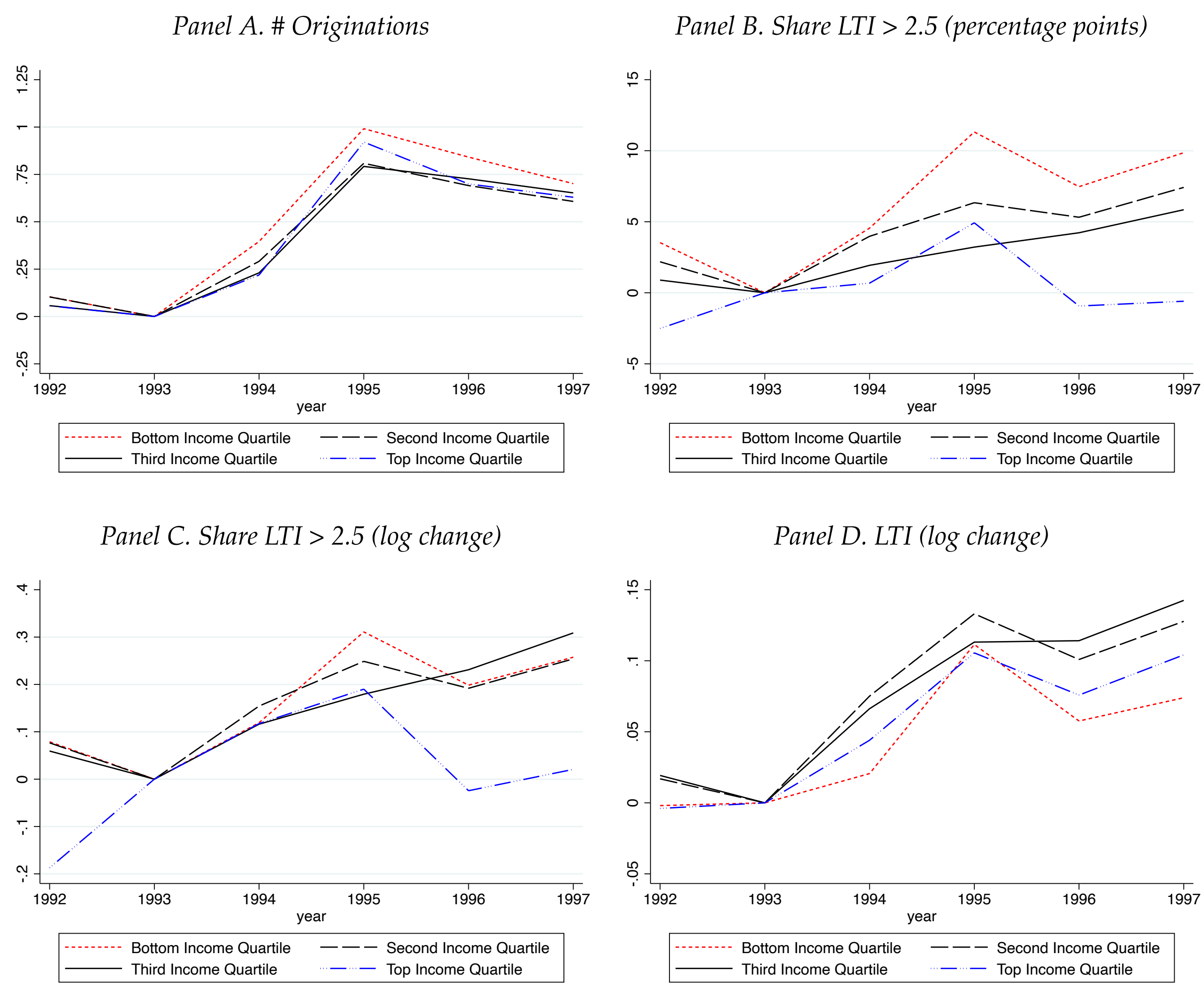
Panel D. LTI (log change)



NOTES: Figure 2A plots estimates of $\{\beta_k\}$ from Equation 3. Figure 2B plots estimates of $\{\beta_k\}$ from Equation 4 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 2C plots estimates of $\{\beta_k\}$ from Equation 5 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 2D plots estimates of $\{\beta_k\}$ from Equation 5 where the dependent variable is the LTI ratio. 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

MORTGAGE CREDIT OUTCOMES FOR INITIAL LP USERS BY BORROWER INCOME QUARTILE (RELATIVE TO INITIAL DU USERS)

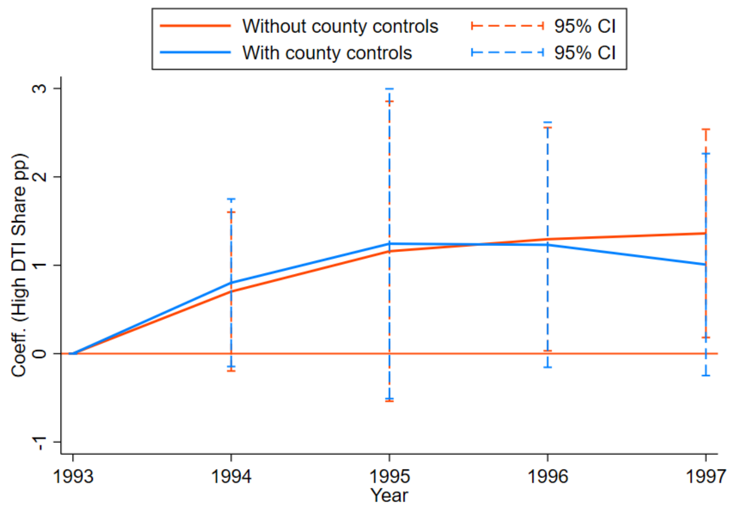


NOTES: See the notes for Figure 2. This figure plots estimated responses separately for each borrower income quartile. Sources: HMDA and authors' calculations.

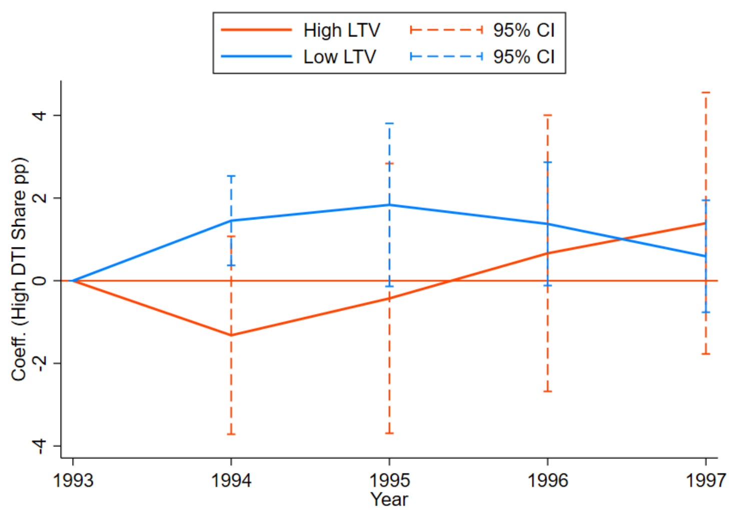
FIGURE 4

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

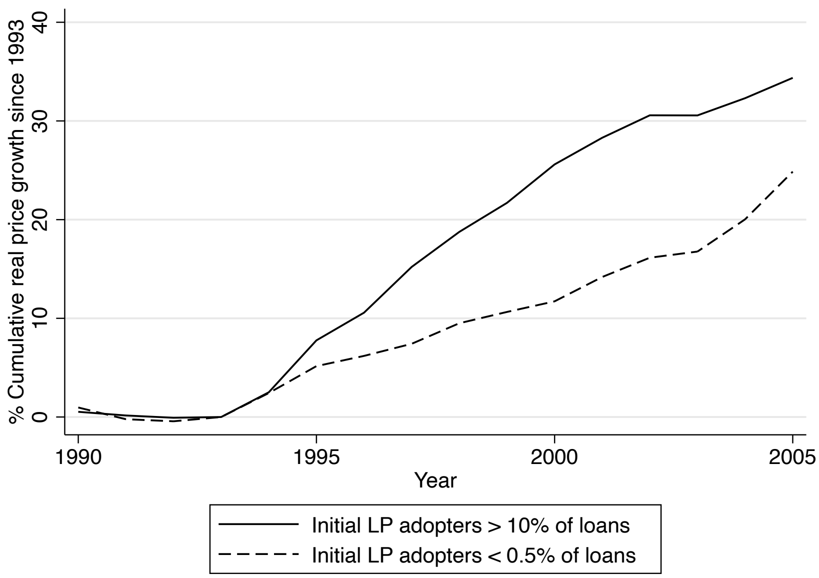


NOTES: This figure plots estimates of $\{\beta_k\}$ from Equation 6. In Figure 4B we split the sample by the loan-to-value ratio. 'High LTV' loans have an LTV ratio above 80 per cent (i.e. down payment of less than 20 per cent). 'Low LTV' loans have an LTV ratio of 80 per cent or below (i.e. down payment 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 4A shows the estimates with and without additional county level controls interacted with year dummies (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). Sources: McDash; HMDA; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

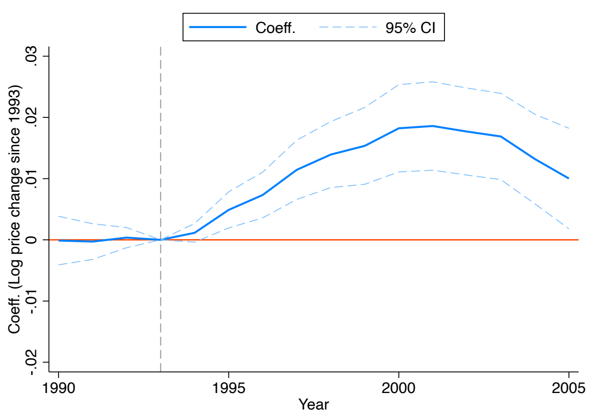
FIGURE 5

EFFECT OF COUNTY EXPOSURE TO INITIAL LOAN PROSPECTOR USERS ON HOUSE PRICES

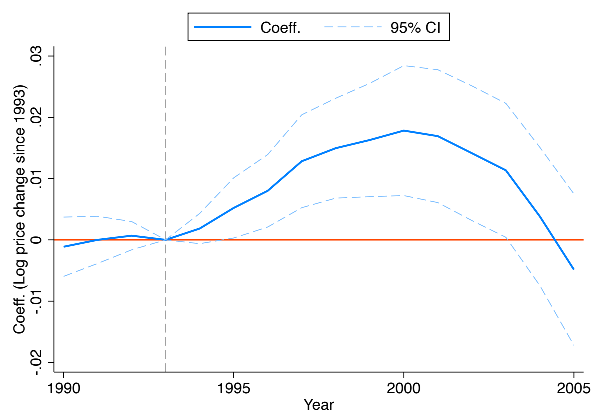
Panel A. The housing boom started earlier in exposed areas



Panel B. Cumulative response relative to all lenders



Panel C. Cumulative response relative to DU users

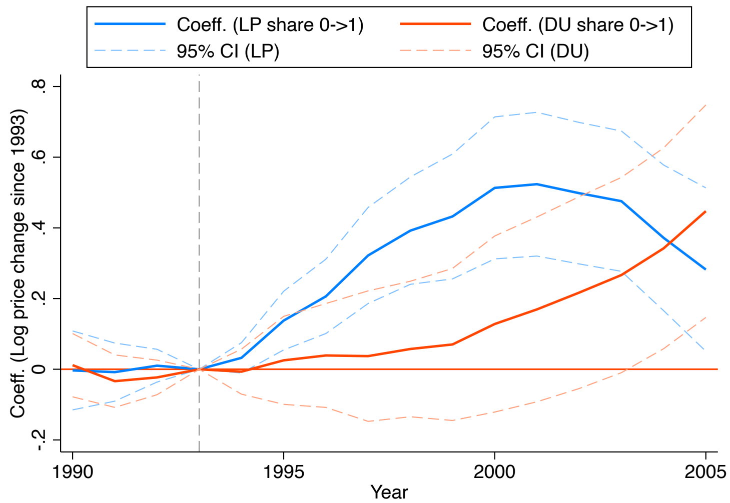


NOTES: Figures 5B and 5C plot estimates of $\{\beta_k\}$ from Equation 8. Both 5B and 5C condition on the following county variables interacted with year dummies: coastal indicator, log median household income, log number of lenders, large lender market share, ratio of housing costs to income, log median property value, share with a bachelors degree or higher. Estimates in Figure 5C are also conditional on the combined county share of initial DU and LP users $EarlyLPorDU_c$. 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; NOAA list of coastal counties; and authors' calculations.

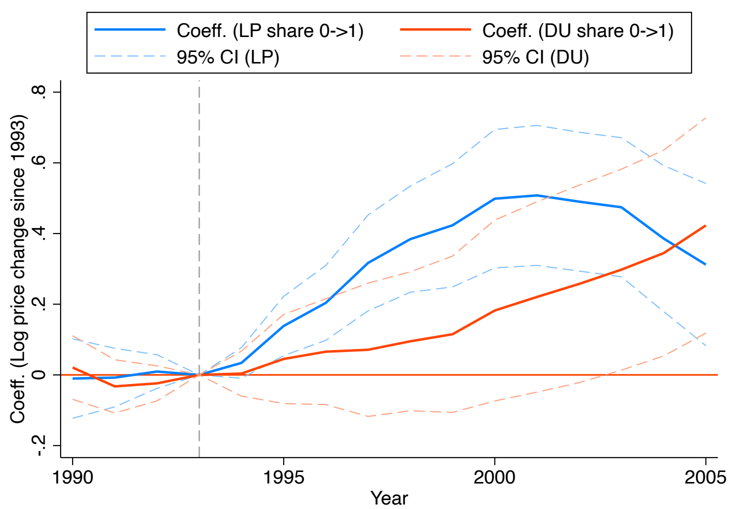
FIGURE 6

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

Panel A. Cumulative response relative to all lenders



Panel B. Cumulative response relative to matched lenders



NOTES: Figures 6A and 6B plot estimates of $\{\beta_k\}$ from: $\log(Price_{c,t}) = \delta_c + \gamma_{d,t} + \sum_{\substack{k=1990 \\ k\neq 1993}}^{2005} \mathbb{1}_{k=t}\left(\beta_k Exposure_c + \alpha_k X_c\right) + \epsilon_{c,t}$, 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 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. Estimates in Figure 6B 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.

TABLE 1
INITIAL LOAN PROSPECTOR USERS

Lender Name	Other names	Lender Type	Share
Citicorp Mortgage		Commercial BHC subsidiary	0.06%
First Security Savings Bank	Flagstar Bank	Thrift	0.69%
Midland Financial Mortgages	AmerUS	IMB**	0.09%
Mission Hills Mortgage Corp.		IMB	0.08%
Monument Mortgage		IMB	0.02%
Mortgage America		IMB	0.03%
Old Kent Mortgage Co.		Commercial bank subsidiary	0.39%
PHH Mortgage Corp.		IMB	0.76%
Standard Federal Bank	InterFirst	Thrift	1.02%

NOTES: This table shows the national market share of early Loan Prospector users by number of 1996 HMDA originations and purchases. The list of early Loan Prospector users was obtained from American Banker (1995). We track mergers, acquisitions and name changes over the sample period using data from the National Information Center (NIC). 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. Sources: HMDA and authors' calculations.
** Independent Mortgage Bank

TABLE 2
INITIAL DESKTOP UNDERWRITER USERS

Lender Name	Other names	Lender Type	Share
American City Mortgage Corp.		IMB**	0.02%
BancBoston Mortgage Corp.		Commercial bank subsidiary	1.27%
BrooksAmerica Mortgage Corp.		IMB	0.03%
Crestar Mortgage Corporation		Commercial bank subsidiary	0.32%
Crossland Mortgage Corp.		Commercial bank subsidiary	0.34%
Fleet Mortgage Corp.		Commercial bank subsidiary	1.88%
Headlands Mortgage Co.		IMB	0.15%
ICM Mortgage Corp.	Pulte Mortgage	IMB	0.11%
National Pacific Mortgage Corp.		Commercial bank subsidiary	0.12%
Phoenix Mortgage and Investment		IMB	0.03%
Residential Funding Corp.	GMAC, GMAC-RFC	IMB	1.06%
Seattle Mortgage Company		IMB	0.02%
Temple-Inland Mortgage Corp.		Thrift subsidiary	0.18%
Trustmark National Bank	Trustmark Corp.	Commercial bank	0.11%
Universal American Mortgage Co.		IMB	0.03%
Washtenaw Mortgage Company		IMB	0.07%

NOTES: This table shows the national market share of early Desktop Underwriter users by number of 1996 HMDA originations and purchases. The list of early Desktop Underwriter users was obtained from a press release (PR Newswire, 1995). We track mergers, acquisitions and name changes over the sample period using data from the National Information Center (NIC). We exclude two lenders that were not HMDA reporters after 1995. These two lenders are West Jersey Community Bank, which was acquired by Sovereign Bank, FSB, and State savings bank, which was acquired by Fifth Third. 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. Sources: HMDA and authors' calculations.
** Independent Mortgage Bank.

TABLE 3
LENDER CHARACTERISTICS BY SYSTEM

	All	LP Users	DU Users
Share sold to Freddie (1991-1993)	0.36	0.54	0.27
	(0.43)	(0.26)	(0.25)
Average loan-to-income ratio (1991-1993)	1.45	2.04	1.94
	(0.73)	(1.26)	(0.37)
Portfolio share (1991-1993)	0.54	0.26	0.23
	(0.35)	(0.27)	(0.29)
Thrift or thrift subsidiary	0.31	0.22	0.12
	(0.46)	(0.44)	(0.34)
Share bottom quartile income (1991-1993)	0.23	0.17	0.15
	(0.14)	(0.10)	(0.08)
Share LTI > 2.5 (1991-1993)	0.10	0.16	0.23
	(0.11)	(0.14)	(0.13)
Conventional share of originations (1991-1993)	0.89	0.89	0.74
	(0.21)	(0.15)	(0.21)
Refinance share of originations (1991-1993)	0.67	0.65	0.59
	(0.20)	(0.14)	(0.17)
Number of Observations	4,140	9	16

NOTES: This table shows descriptive statistics for lenders listed in Tables 1 or 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 (1991-1993)	0.36**	0.59**
	(0.14)	(0.21)
Average loan-to-income ratio (1991-1993)		0.04
		(0.18)
Portfolio share (1991-1993)		0.06
		(0.14)
Thrift or thrift subsidiary		-0.13
		(0.12)
Share bottom quartile income (1991-1993)		0.14
		(0.31)
Share LTI > 2.5 (1991-1993)		-0.15
		(0.16)
Conventional share of originations (1991-1993)		0.14
		(0.17)
Refinance share of originations (1991-1993)		-0.24
		(0.19)
Number of Observations	25	25

NOTES: This table shows estimated coefficients from $LP_l = \alpha + \beta X_l + \epsilon_l$. LP_l is an indicator equal to 1 for initial Loan Prospector users listed in Table 1 and zero for initial Desktop Underwriter users listed in 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 (1996)	3.0	4.8	1.3
	(3.6)	(4.3)	(0.5)
Share of population living in NOAA coastal county (1990)	37.3	41.3	33.3
	(48.4)	(49.3)	(47.2)
Median household income (000s,1989)	30.1	31.6	28.6
	(6.9)	(7.4)	(6.0)
# HMDA Respondents (1996)	191.6	207.7	175.4
	(106.8)	(115.0)	(95.3)
Market share of large HMDA respondents (1996)	28.1	30.3	25.9
	(9.7)	(9.2)	(9.7)
Ratio of owner (with mortgage) housing costs to income (1990)	28.1	27.9	28.2
	(4.0)	(4.1)	(3.9)
Share of persons 25+ with bachelors degree or higher (1990)	18.6	20.1	17.1
	(7.8)	(8.2)	(7.2)
Median value of owner-occupied housing (000s,1990)	79.4	85.5	73.3
	(42.6)	(47.5)	(36.0)
Number of Observations	882	441	441

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 (1990)	0.22***	0.12***
	(0.07)	(0.04)
Log median household income (1989)	-0.08	-0.09
	(0.10)	(0.09)
Log # HMDA Respondents (1996)	-0.03	0.04
	(0.04)	(0.04)
Market share of large HMDA respondents (1996)	0.39***	0.04
	(0.07)	(0.06)
Ratio of owner (with mortgage) housing costs to income (1990)	-0.21***	-0.17***
	(0.07)	(0.07)
Log median owner-occupied home value (1990)	-0.08	-0.05
	(0.10)	(0.09)
Share of persons 25+ with bachelors degree or higher (1990)	0.13***	0.03
	(0.04)	(0.03)
Market share of early LP or DU users by # of loans (1996)		0.67***
		(0.10)
Division FE	X	X
Number of Counties	882	882
Number of States	51	51
Within R-squared	0.14	0.52
Number of Observations	882	882

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 1 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 User X Post	-6.422***	-6.656***	-5.049***
	(-5.49)	(-3.45)	(-4.53)
Lender × Income Quartile FE	X	X	X
Number of Observations	2,287,480	1,554,424	3,841,905

NOTES: This table shows estimates of β from Equation 7. 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 ***. 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 $\times$ Post	1.05***	1.00***	0.49***	0.57***	1.67***	1.87***
	(0.22)	(0.33)	(0.12)	(0.17)	(0.33)	(0.52)
Number of Counties	710	710	710	710	710	710
Number of States	51	51	51	51	51	51
Number of Observations	1,420	1,420	1,420	1,420	1,420	1,420

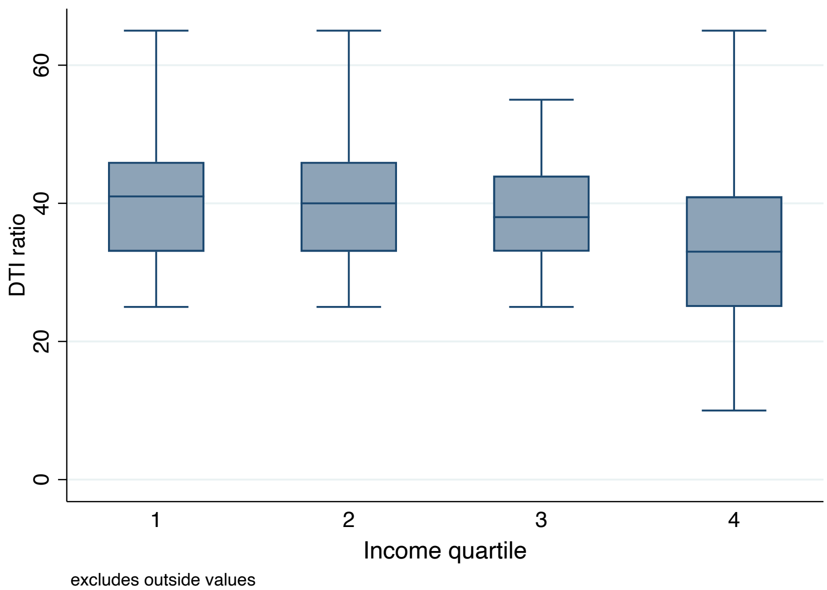
NOTES: Columns 1-4 show estimates of β from $Y_{c,t} = \delta_c + \gamma_{d,t} + \beta LP_c \text{Post}_t + \alpha X_c \text{Post}_t + \epsilon_{c,t}$. Columns 5-6 show estimates of β from $Y_{c,t} = \exp\left(\delta_c + \gamma_{d,t} + \beta LP_c \text{Post}_t + \alpha X_c \text{Post}_t\right) + \epsilon_{c,t}$. 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.

Online Appendix

Financial Technology and the 1990s Housing Boom

Stephanie Johnson Nitzan Tzur-Ilan

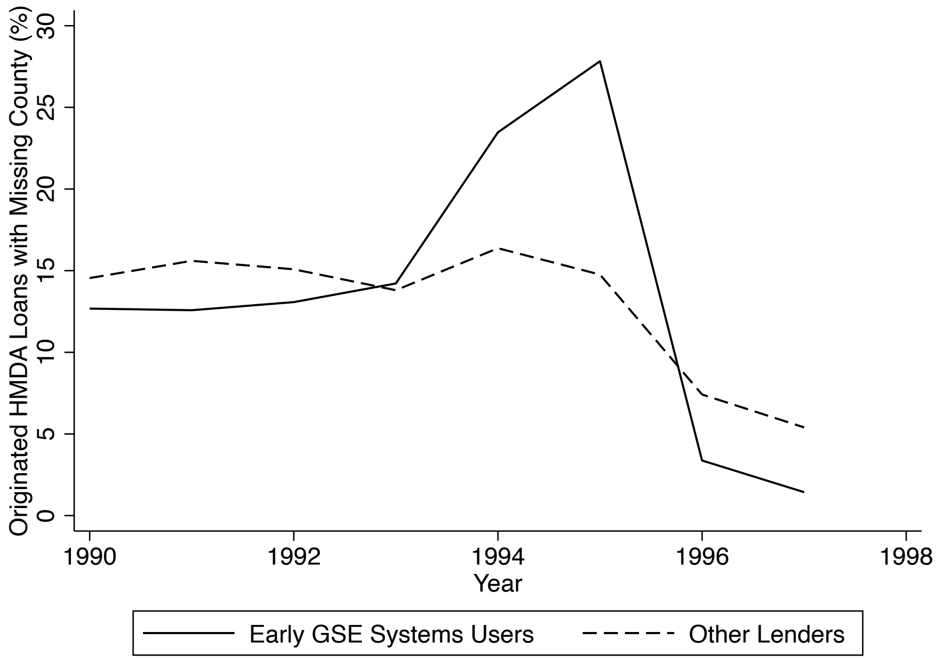
FIGURE A.1
DEBT-TO-INCOME DISTRIBUTION BY INCOME QUARTILE



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 A.2

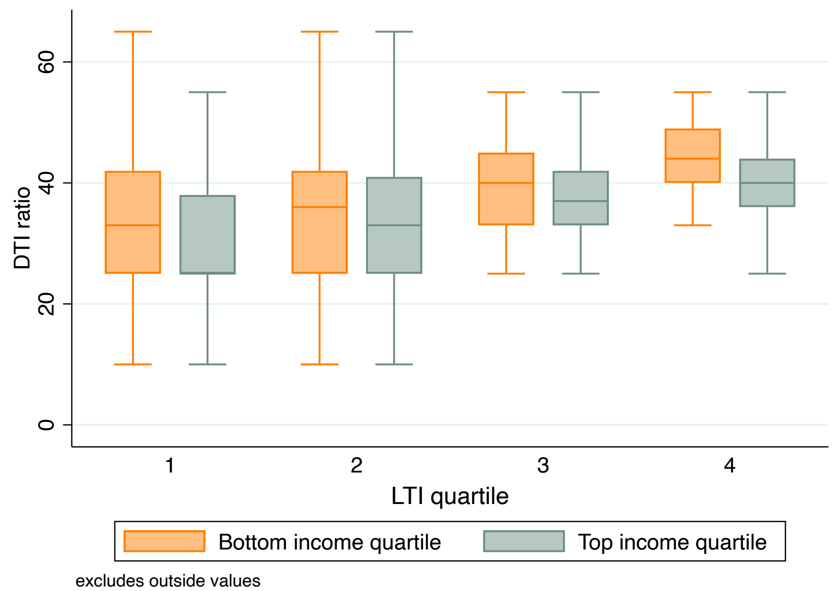
SHARE OF HMDA ORIGINATIONS FOR WHICH THE PROPERTY LOCATION IS UNREPORTED



NOTES: This figure is constructed using HMDA originations from 1990–1997. Early GSE systems users are the lenders listed in Table 1 or 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 A.3

RELATIONSHIP BETWEEN DEBT-TO-INCOME AND LOAN-TO-INCOME RATIOS

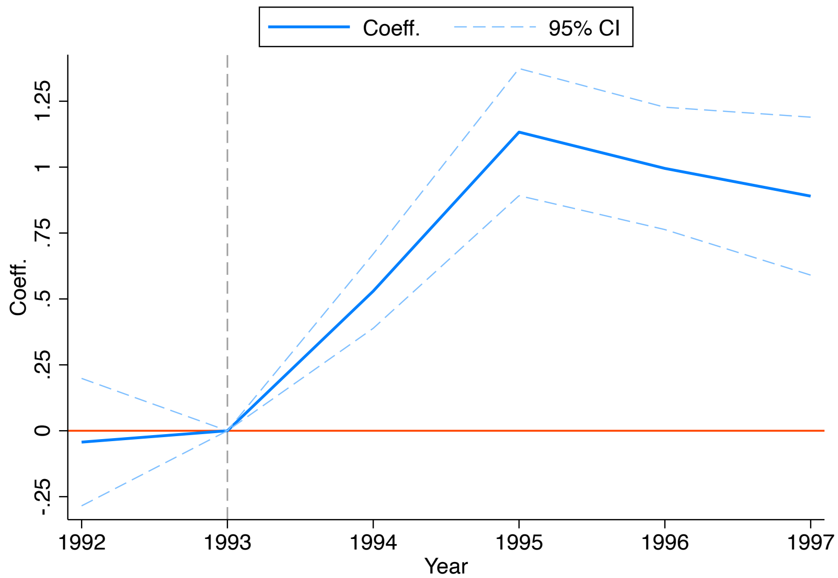


NOTES: This figure is constructed using 2018 HMDA home purchase originations. DTI ratios are top-coded at 60 per cent. Where DTI ratios are binned we assume the DTI is equal to the bin midpoint. LTI is loan size divided by annual income. DTI is reported by the lender and is the ratio of monthly mortgage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

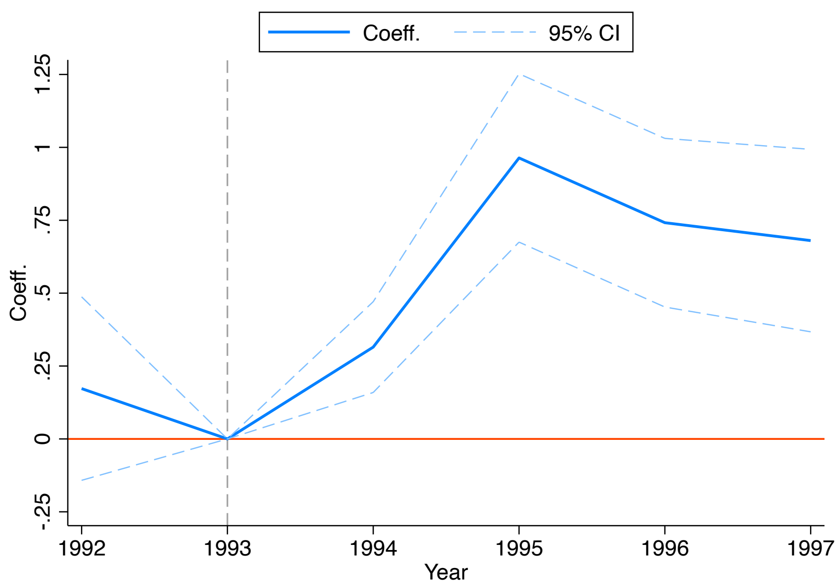
FIGURE A.4

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

Panel A. # Purchase originations



Panel B. # Refinance originations

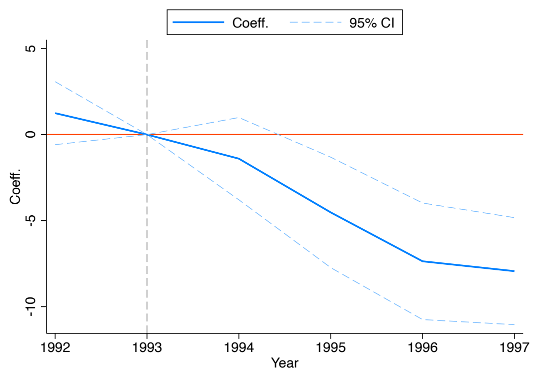


NOTES: This figure is constructed in the same way as Figure 2A but the sample is restricted to home purchase originations in Figure A.4A and refinance originations in Figure A.4B. Refer to the notes to Figure 2 for additional details. Sources: HMDA and authors' calculations.

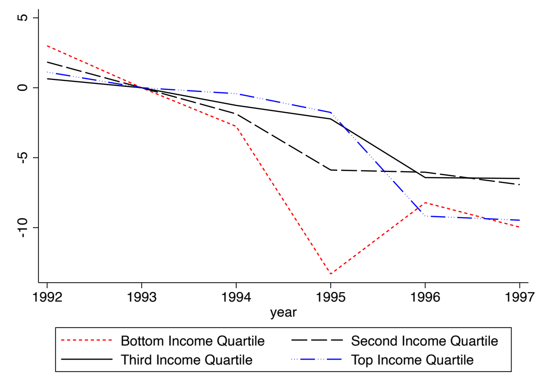
FIGURE A.5

MORTGAGE DENIAL PROBABILITY FOR INITIAL LOAN PROSPECTOR USERS (RELATIVE TO INITIAL DESKTOP UNDERWRITER USERS)

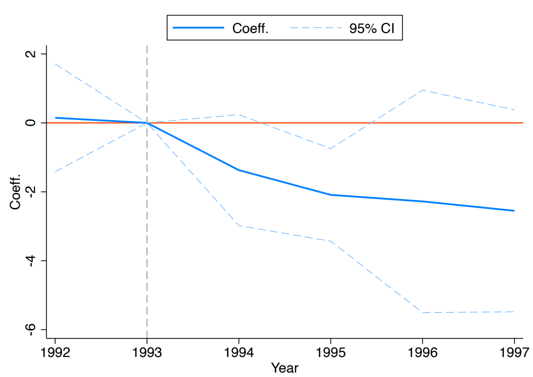
Panel A. With county by year fixed effects (pp)



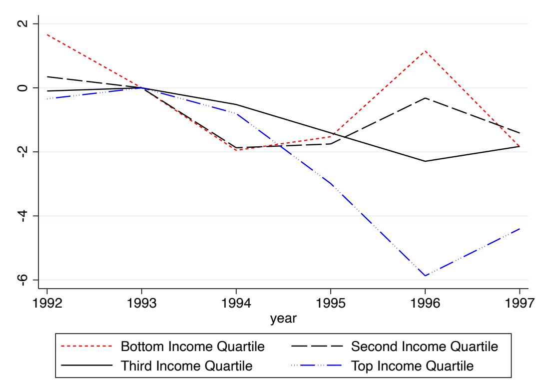
Panel B. With county by year fixed effects; by income quartile (pp)



Panel C. Without location fixed effects (pp)

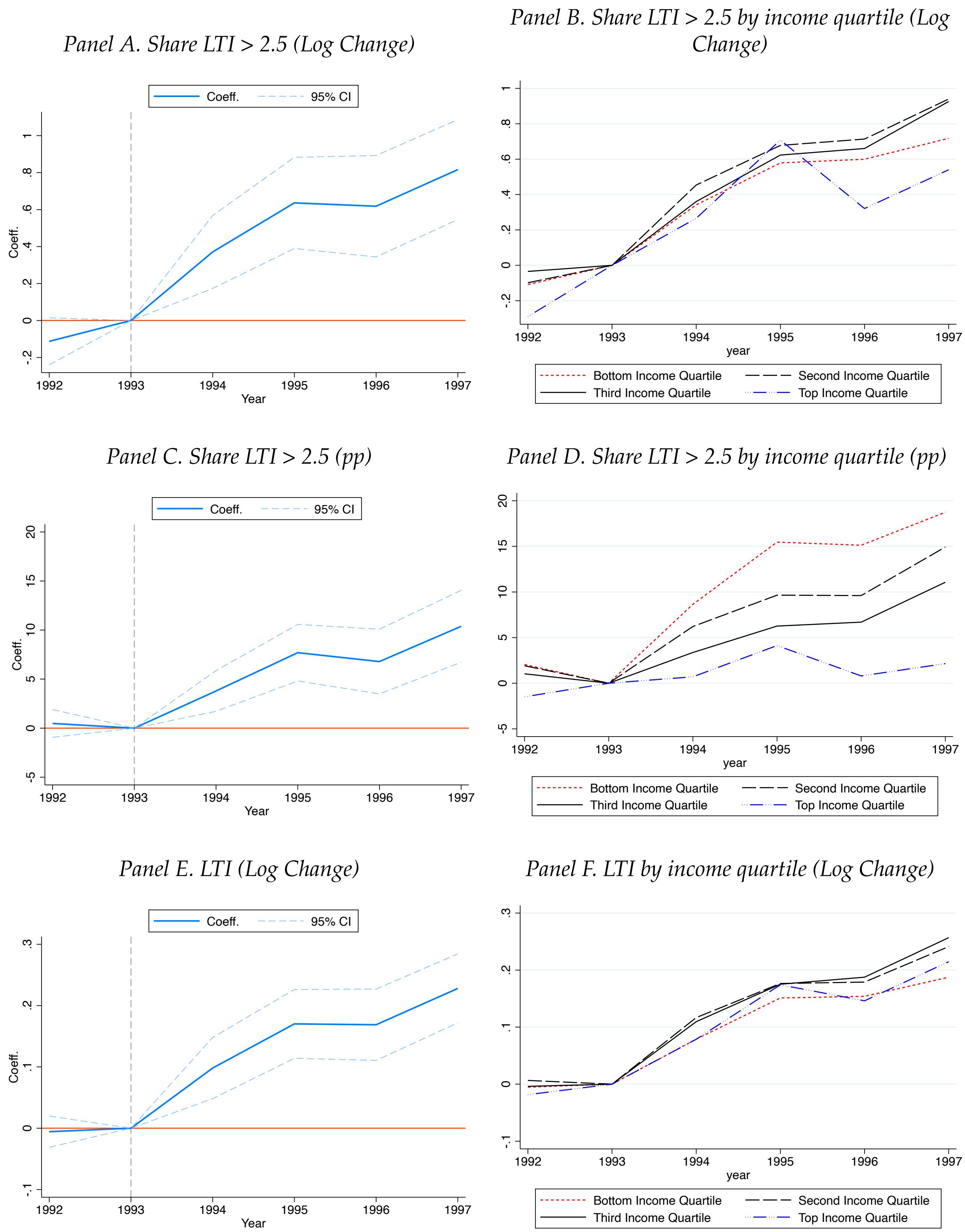


Panel D. Without location fixed effects; by income quartile (pp)



NOTES: This figure plots estimates of $\{\beta_k\}$ from Equation 4 where the dependent variable is an indicator equal to one for denied applications and zero for originated loans. Sources: HMDA and authors' calculations.

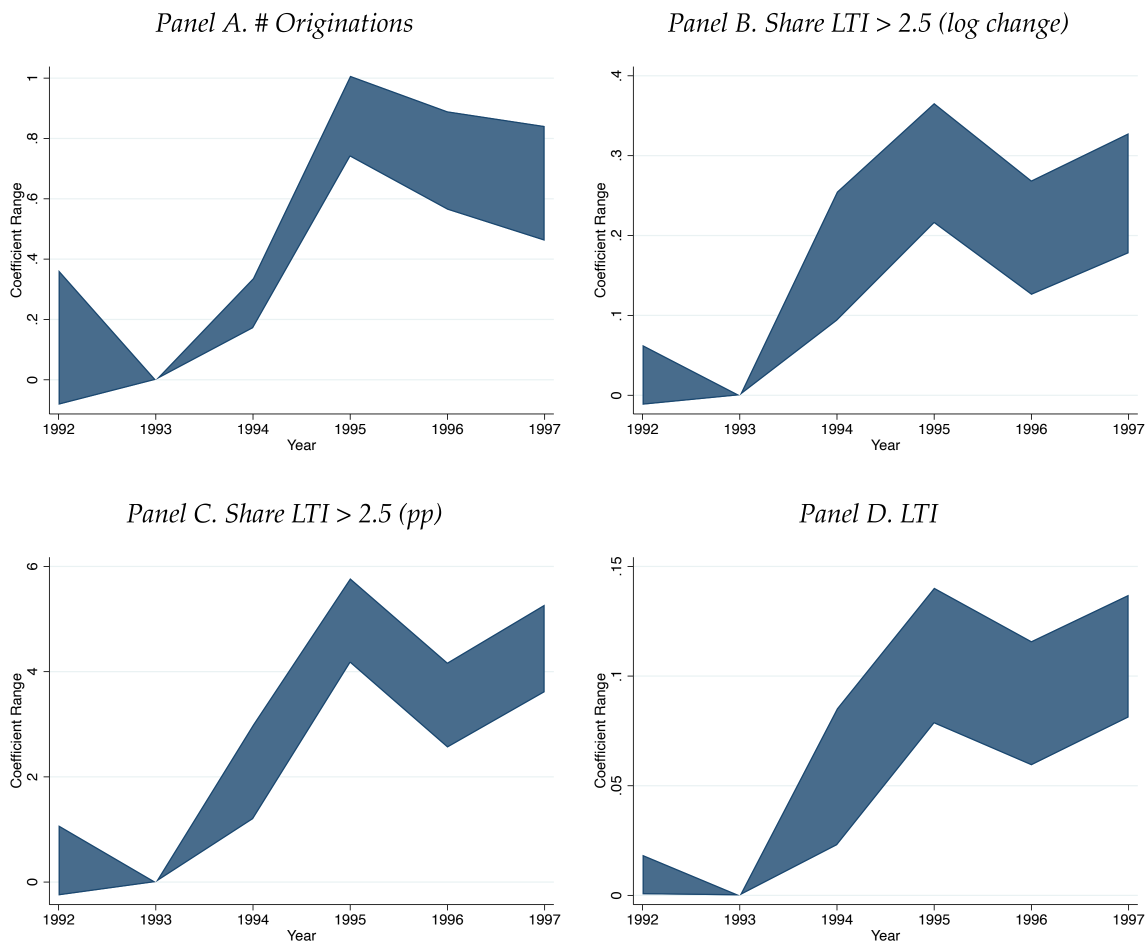
FIGURE A.6
ESTIMATED CREDIT RESPONSE WITHOUT LOCATION FIXED EFFECTS



NOTES: Refer to the notes to Figures 2 and 3. 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 A.7

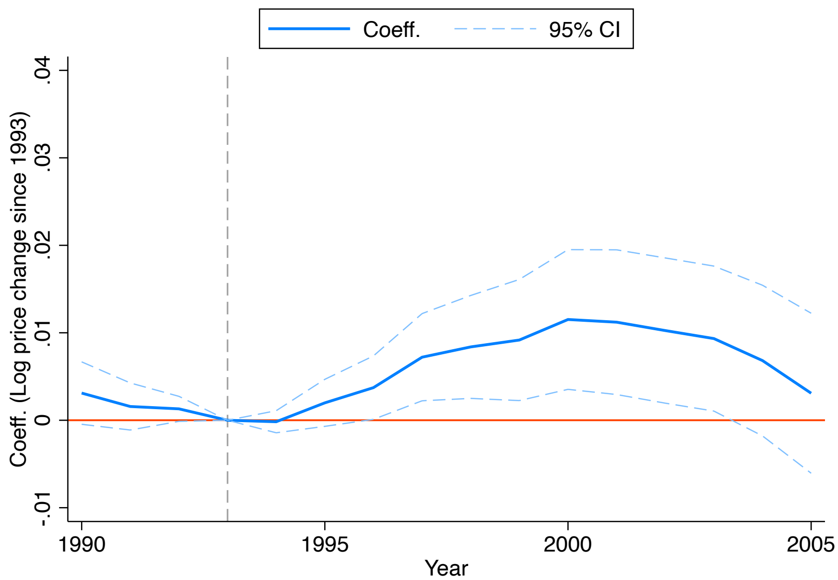
RANGE OF CREDIT ESTIMATES WHEN DROPPING LENDERS ONE AT A TIME



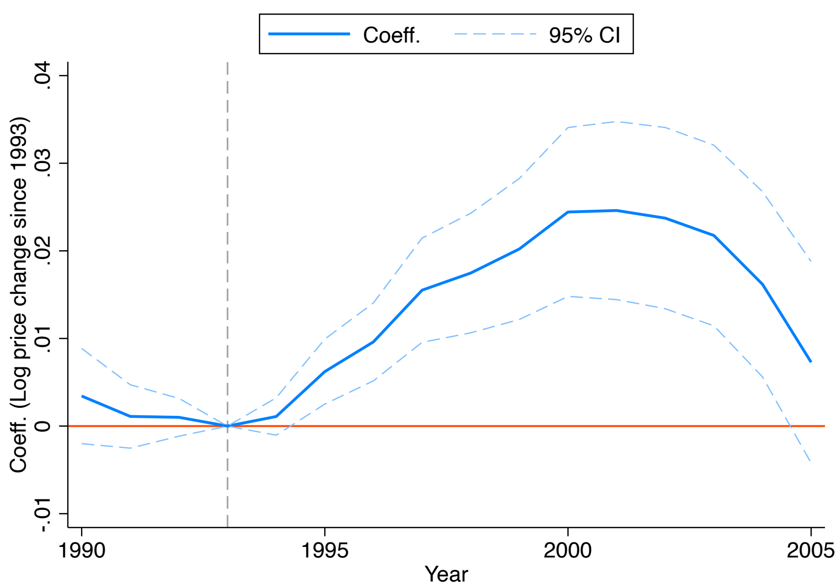
NOTES: Refer to the notes to Figure 2. We re-estimate the responses in Figure 2 with one lender dropped each time, and plot the range of estimated coefficients. Sources: HMDA and authors' calculations.

FIGURE A.8
RESPONSE OF HOUSE PRICES TO LOAN PROSPECTOR ADOPTION (1993 EXPOSURE)

Panel A. Relative to all lenders



Panel B. Relative to initial DU users

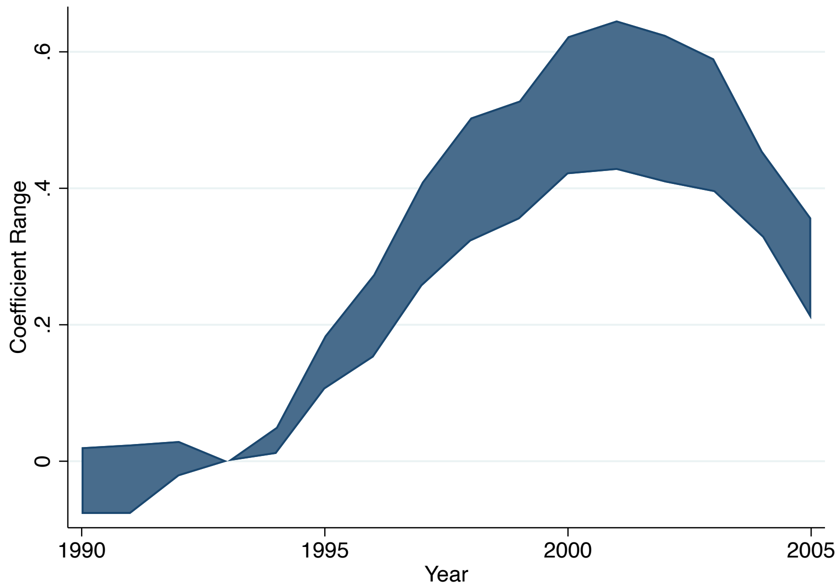


NOTES: Panel This figure plots estimates of $\{\beta_k\}$ from Equation 8 using an alternative exposure measure computed using 1993 HMDA data ($EarlyLP_{c,1993}$). Figure A.8B also conditions on $EarlyLPorDU_{c,1993}$ interacted with year dummies. See the notes to Figure 5 for additional details. Sources: FHFA HPI; HMDA; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

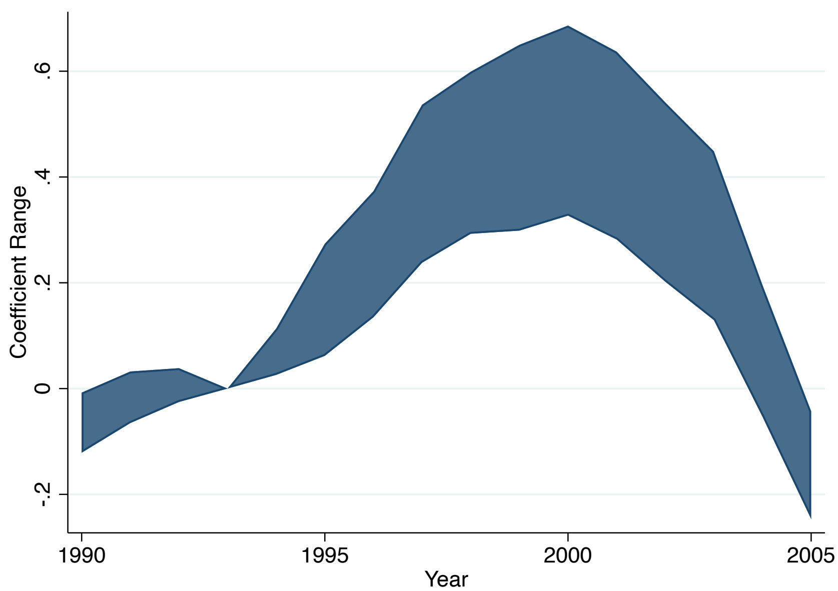
FIGURE A.9

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

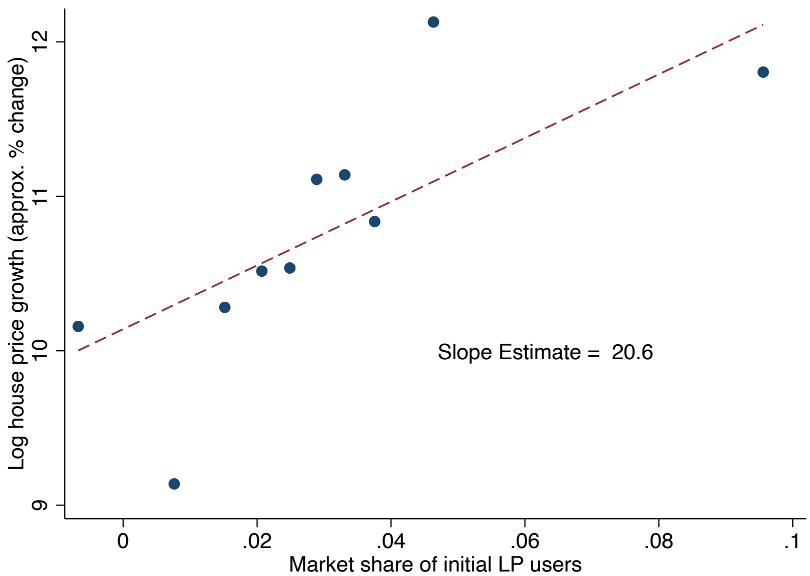


NOTES: This figure is constructed by re-estimating the coefficients reported in Equation 10 with one lender dropped each time before computing the exposure measure. Figure A.9B also conditions on $ShareLPorDU_c$ interacted with year dummies. Sources: FHFA HPI; HMDA; 1990 decennial census; NOAA list of coastal counties; and authors' calculations.

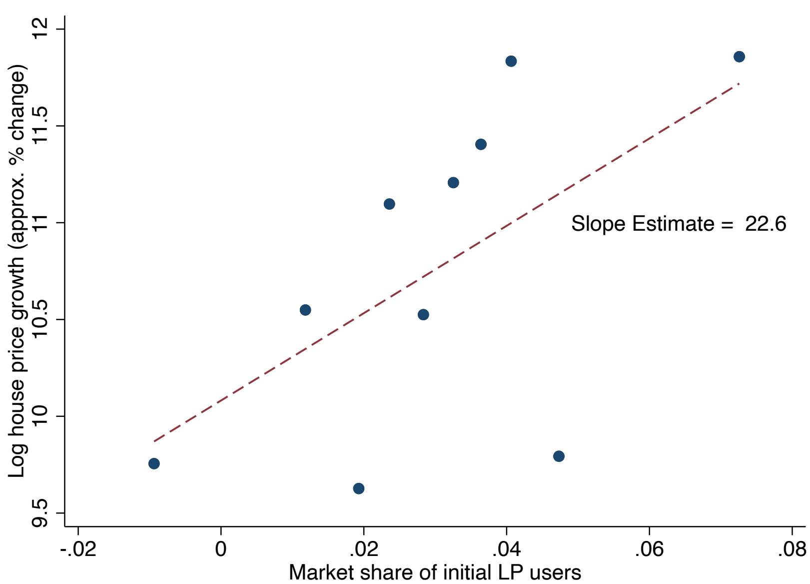
FIGURE A.10

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 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) and census division fixed effects. Figure A.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.

TABLE A.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 A.2
INITIAL DU USERS AND MATCHED CONTROL LENDERS

Dependent variable: 1 for initial DU users and 0 for matched control lenders.

	(1)	(2)	(3)
Share sold to Fannie or Freddie (1991-1993)	0.27	0.76***	
	(0.20)	(0.26)	
Average loan-to-income ratio (1991-1993)		0.01	0.08
		(0.17)	(0.18)
Share LTI > 2.5 (1991-1993)		0.17	0.06
		(0.16)	(0.17)
Portfolio share (1991-1993)		0.14*	0.02
		(0.07)	(0.07)
Share bottom quartile income (1991-1993)		0.10	0.08
		(0.07)	(0.07)
Conventional share of originations (1991-1993)		-0.05	0.03
		(0.08)	(0.08)
Refinance share of originations (1991-1993)		-0.01	-0.00
		(0.06)	(0.07)
Share of loans purchased (1991-1993)		0.03	0.03
		(0.06)	(0.06)
Adjusted R-squared	0.01	0.09	-0.03
Number of Observations	64	64	64

NOTES: This table shows coefficient estimates from $\text{DU}_l = \alpha + \beta X_l + \epsilon_l$. DU_l is an indicator equal to 1 for initial DU users listed in Table 2 and zero for the matched control group. 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 A.3

CORRELATION BETWEEN AUS USAGE AND PROCESSING TIME

Dependent variable: Days from application to closing/denial.	(1) Originated	(2) Denied	(3) All
AUS Used	-1.128***	14.79***	6.030***
	(-39.85)	(173.65)	(228.43)
Number of Observations	5,886,119	924,717	6,810,836

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.