Electronic Foreclosures

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Abstract

This paper investigates how technology affects collateral liquidity in mortgage markets. Exploiting the staggered introduction of electronic bidding across Florida's counties, I show that foreclosure auction success increases by 27%, and price discounts shrink by 42%. Electronic auction winners are more likely to be local non-professionals, who are found to flip acquired properties less often ex-post. I also find that credit supply expands and mortgage loan rates decrease, consistent with lenders incorporating lower foreclosure costs into lending decisions. Overall, this evidence suggests that technological modernization can improve allocative efficiency in real estate markets, deepen liquidity, and foster financial inclusion.

Keywords: Electronic marketplace, Online auction, Mortgage foreclosure;

JEL: G21; O33; D44;

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1 Introduction

Search frictions can generate poor buyer-asset matches and inefficiently depress prices. One such market friction is the presence of participation costs, which may constrain potential bidders in terms of pool size and composition. Such inefficiencies may be particularly severe in the case of forced asset sales, as the best-suited buyer is unlikely to be readily available at short notice (Shleifer and Vishny, 1992). Participation frictions may lead to adverse selection, market segmentation, and resource misallocation (Gurley and Shaw, 1960; Diamond, 1982; Allen and Santomero, 1997), and amplify negative price spillovers and feedback loops associated with asset liquidations (Kiyotaki and Moore, 1997; Asquith et al., 1994; Brunnermeier and Pedersen, 2009).

In this paper, I examine how technology (electronic bidding) can lower buyer participation costs and enhance collateral liquidity and valuation in U.S. mortgage credit markets. Lenders are entitled to recover the value of their outstanding mortgage loan by seizing and selling the house of defaulting borrowers under a foreclosure process. Foreclosures are ideal to study participation frictions, since the sales of mortgaged properties in U.S. judicial states have been traditionally conducted using live public auctions at the premises of the county courthouse (Burkhart, 2017). Although the foreclosing lender (typically a bank) has the obligation to attend the auction, third-party participation is voluntary and, most importantly, quite costly. Potential buyers are required to travel to the courthouse for bidding at specific dates. Moreover, information about the quality of the property is not readily available to them, as home inspection is not permitted before auction (Niedermayer et al., 2015). As a result, bidding competition at auctions is scarce, and the foreclosing lender itself ends up purchasing the foreclosed property in more than 80% of auctions (Burkhart, 2017).

I take advantage of a legal reform that changed the foreclosure process to identify the effect of lowering participation frictions on foreclosure sales. To reduce court administrative costs, in the summer of 2008 Florida has become the first U.S. state to modify its statute and allow its counties to switch from in-person auctions to electronic bidding.[1] The switch to the new technology is not mandatory for counties under the new law, but if adopted, the bidding format is the only feature of the foreclosure process that changes. In particular, information availability remains constant.

I find electronic bidding to lead to a 5 percentage point increase in foreclosure auction success and to a 3 percentage point decline in auction discount. When compared to the sample average auction success and discount of houses entering the foreclosure auction stage, these estimates represent a 27% increase and a 42% decrease, respectively, which are economically sizable. The results suggest that electronic bidding considerably improves liquidity in the foreclosure market.

The online technology benefits foreclosing lenders with quicker and less costly foreclosure sales. Accordingly, lenders save asset ownership expenses.[2] But there are also social benefits because better foreclosure outcomes improve the allocation of assets from the banking sector, which is holding troubled assets, to the household sector, which is buying them. In fact, banks frequently hold foreclosed properties in a neglectful way – which hurts neighboring property owners and the community (Harding et al., 2009; Campbell et al., 2011; Lin et al., 2009) – whereas households can derive utility from possessing the house. Considering the opportunity cost of a vacant property, brokerage sale commissions, and inventory costs avoided, I determine with a back-of-the-envelope calculation that the estimated increase in foreclosure auction success generates substantial welfare gains (at least 0.56 basis point of GDP).[3]

For identification, I use a within-state difference-in-differences (DiD) design, comparing affected counties to adjacent non-affected counties around an adoption date. Such a strategy prevents confounding effects resulting from discrepancies in state-level

[1] At the time of writing, Florida and Ohio are the only two states in the U.S. as of yet permitting county courts to conduct electronic foreclosure auctions. However, most counties in Ohio adopted the state policy (Bill 390) during the Covid-19 pandemic, making an empirical assessment of electronic auctions more difficult.

[2] After no third parties buy at the foreclosure auction, the property becomes a Real Estate Owned (REO) asset in the balance sheet of the bank. REO expenses include maintenance and selling costs, and can total up to 15.95% of property value. See https://www.benefits.va.gov/homeloans/servicers_valeri.asp.

[3] There are also indirect benefits the improved sale technology most likely brings: defaulting borrowers suffer smaller deficiency judgements, fire-sale spillovers are lower in neighborhoods and the community therein. These analyses are outside the scope of this paper.

foreclosure laws to bias the estimates. To circumvent the bias of the staggered DiD estimators (Baker et al., 2021), I adopt the "stacked regression" approach (Cengiz et al., 2019). I obtain novel public tax roll property-level data spanning the years 2009-2019 from Florida Department of Revenue. To measure the foreclosure discount, I use the county assessor's opinion of the annual market value of each residential property, which considers all its tangible and intangible conditions.

The present study relies on the implementation of a Florida state bill that counties adopted at different points in time (if at all). Anecdotal evidence indicates that policy adoption was primarily meant to eliminate court labor costs, paper-based processes, and unforeseen events (e.g., tropical storms, fire drills, power outages, etc.) that disrupted live auctions.[4] If indeed implemented for court efficiency reasons, the change in bidding format is exogenous to the outcome variables I study. While anecdotal evidence helps in mitigating endogeneity, it is not perfect and concerns about reverse causality may remain. Motivated by the anecdotal evidence, I also use an instrumental variable (IV) approach with the court backlog as an instrument for electronic bidding adoption. The idea is that when non-foreclosure departments expect not to "keep up" with their civil non-mortgage caseload, the whole court benefits more to decentralize and automatize some of their workload (i.e., conducting foreclosure auctions). The exclusion restriction is unlikely to be violated since accumulated court pressure resulting from non-mortgage civil cases does not relate to auction participation. The IV exercise confirms the positive effects of electronic bidding.[5]

I continue by investigating the mechanisms through which the collateral liquidity resulting from the implementation of electronic bidding increases. I find that once online auctions become available, the share of volume buyers and that of professional investors in the composition of auction buyers decrease. These types of agents generally are more likely to be motivated by financial returns (e.g., buy-to-let, renovate

[4] The anecdote is based on conversations with case managers of Florida courthouses. Also, this sentiment was present in media articles (e.g., see here: https://www.builderonline.com/money/mortgage-finance/florida-courts-can-now-conduct-foreclosure-sales-online_o

[5] The DiD coefficient under 2SLS estimation is found to be larger than the one under OLS. If the adoption was the response to poor foreclosure outcomes in the county, OLS estimates would have given upwardly biased estimates (bouncing) of the true effects of online auctions.

and turn over).[6] Instead, new buyers, i.e. non-professional individuals, may view the asset as a consumption good rather than an investment. This result —which is novel in the digital finance literature—suggests that technological advances may have enabling functions, empowering retail individuals at the expense of specialized professional intermediaries. In the foreclosure setting, this is plausible given the relatively larger participation frictions for non-professional individuals at live auctions. Moreover, I find the electronic bidding technology to increase the probability that bidders already living in areas close to the property win the auction.[7] Arguably, these are the users with the highest valuation for the property. Local buyers may have a personal preference for the neighborhood since they already chose to reside and possibly work there. Therefore, they may be better able to evaluate the value of the house (e.g., more knowledgeable about pollution, attractive shops nearby, noise, etc.). Overall, these results suggest that electronic bidding facilitates allocating a troubled asset to its best-suited holder.

Next, I study whether ex-ante decisions in mortgage credit supply incorporate the improvement in future foreclosure outcomes. An increase in collateral liquidation payoffs lowers the cost of extending credit for banks (Benmelech et al., 2005; Pence, 2006). Using borrower application-level data, I find that in affected counties mortgage lending increases by 2.77%. This effect is even more pronounced in the risky borrower segment of the mortgage market. Furthermore, lenders start charging lower rates on accepted mortgage loans in affected counties. These results suggest that in-person foreclosure auctions impose material costs on borrowers at the time of loan origination.

Finally, I explore heterogeneous effects of electronic bidding on auction success

[6] Therefore, online bidding helps owner-occupants to acquire a home in a cost-effective way. The cost savings potential is found to be the primary motive for most U.S. consumers to acquire a foreclosed home at an action. This factor is particularly important among Millenials, who are also the ones more willing to participate with remote bidding (see https://www.svclnk.com/blog/more-than-three-in-five-us-consumers-would-consider-buying-a-home-at-auction-according-to-new-servicelink-survey/).

[7] Though I cannot rule out that participation rates of more distant buyers increase (data about non-winning bids are observable only for affected counties post-treatment), another reason why electronic bidding reduces buyer-property distance may just be that monetary participation costs are lower than frictions associated with in-person participation (e.g., dealing with the lender's representative, requesting days off at work, non-anonymity).

across geographies, time periods, and property quality. The largest effects are found in counties with more remote courthouses, which is in line with the fact that technology lowers participation hurdles overall. Moreover, the estimates increase for properties that are more distant from the courthouse. If paired with the evidence on reduced buyer-property distance, this result is in line with the idea that local buyers (i.e., those living close to the property, and distant from the courthouse) can use the technology to participate in the foreclosure market. Also, electronic bidding effects are stronger in months with more simultaneous foreclosure auctions, which suggests that technology helps alleviating inefficiencies of simultaneous liquidations (i.e., fire sales). Finally, properties in good conditions benefit the most from online auctions, which is consistent with the fact that non-professional buyers are less likely to immediately refurbish their house for letting it, as they may be more averse to bad quality.

This study contributes to several strands of literature. First, the illiquidity component of distressed sales has been documented in both real and financial asset markets (Pulvino, 1998; Coval and Stafford, 2007; Ellul et al., 2011). In the real estate context, although existing studies exhibit large variations in terms of definitions and estimates, all recognize the presence of a foreclosure price discount (e.g., Campbell et al., 2011; Anenberg and Kung, 2014). The results in this paper suggest one of its determinants is the size and composition of the pool of buyers. Technology can reduce lenders' loss severity by accelerating the allocation of specialized assets to high-valuation users. The literature has also shown that, because of deteriorating property conditions, foreclosed properties create negative price spillovers on non-foreclosed properties nearby (e.g., Immergluck and Smith, 2006), attract crime and vandalism (Lambie-Hanson, 2015), and impose large public and social costs (Ihlanfeldt and Mayock, 2015; Currie and Tekin, 2015). The adoption of electronic bidding technologies helps avoiding long vacancy spells and may, thus, alleviate negative externalities of asset liquidations.

Secondly, the advent of information technology (IT) has transformed the way in which parties trade assets in a marketplace (Bakos, 1997, 1998). The main two functions of IT are: improvements in information and reduction in participation costs. Regarding the former, Jensen (2007) and Gao and Huang (2020) study information production and its effect on price efficiency. The availability of new technology can benefit more sophisticated investors when capacity in information processing matters (for instance, see Hendershott et al., 2011; Menkveld, 2013; O'Hara, 2015, for high-frequency trading). Because the online auction platform does not add any details about the property (e.g., pictures), the technology in this context reduces participation frictions while keeping information constant. Bogan (2008) and Jack and Suri (2014) document positive participation effects of IT, but use survey data and do not study any buyer-asset matching or pricing consequences. This paper contributes to this literature by showing that the introduction of technology enables retail players – whose participation frictions are arguably more severe – to participate in a market. By reducing participation frictions, the digitization of an illiquid market diminishes the advantage of specialized investors (e.g., real estate companies).

Finally, there is an extensive literature in banking showing the benefits of loan resale liquidity. The technology of liquidating loans (e.g., ability to sell loans through securitization in secondary markets) can mitigate the transmission of fund shocks, and weaken banks' sensitivity to interest-rate shocks (Loutskina and Strahan, 2009; Loutskina, 2011). The efficient lending processes of FinTech lenders and the ability of investors to sell *notes* in the secondary market is a modern analogy of technology advances for loan liquidity (Bollaert et al., 2021; Wang, 2018). The results of this paper confirm that banks anticipate expected increases in future loan sales (i.e., electronic foreclosure payoffs) and adjust their ex-ante credit supply and mortgage loan prices (Pence, 2006; Dagher and Sun, 2016; Bongaerts et al., 2021). The mortgage credit context I focus on permits to document important real effects of market digitization.

2 Institutional Background and Hypotheses

This section describes U.S. foreclosure laws and the auction format policy enacted by the state of Florida in the Summer of 2008.

2.1 Foreclosure process

The foreclosure process is the legal procedure through which lenders seize and sell a mortgaged property (collateral) to recoup the loan outstanding balance. In the U.S., the lender mails a notice of default to the borrower after three months of missed mortgage payments. While a property repossession can be expedited and directly handled by a trustee without court involvement in power-of-sale states, lenders have to file a lawsuit to foreclose to the court in judicial states. As Florida is a judicial state, thereafter I describe the judicial process of foreclosures.

County clerks check evidence of default and the outstanding debt amount before approving a Final Judgement amount (i.e., mortgage balance due plus accrued interests and fees) and scheduling an auction date. Judicial review laws protect the borrower because they considerably slow down the foreclosure process and increase legal costs imposed on creditors, such as attorney and court fees, by as much as 10% per loan (Pence, 2006).[8] Each county court requires publication of the foreclosure property advertisement in a local legal newspaper two or three weeks before the scheduled auction.[9] During the pre-auction period, although a "for sale" sign is posted on the property, potential bidders by law cannot inspect inside property conditions. However, people can in the very least drive by the property and visualize the local neighborhood to look for the exterior and landscaping conditions.

At the auction, there are no particular restrictions on bidders, except a one-day in-advance registration and the posting of a deposit. By law any bidder should deposit 5% of their expected winning bid prior to the auction. The design of U.S. foreclosure auctions is an ascending open bid mechanism which, relative to sealed bidding, is known to provide more information to bidders, increase efficiency, and mitigate the winner's curse (Milgrom and Weber, 1982). Foreclosure auctions are fixed reserve: lenders set one week in advance a reserve price ("credit bid"), below

[8] State-level liquidation costs have implications for lenders' incentives to foreclose (Mian et al., 2015; Favara and Giannetti, 2017), and for ex-ante credit supply (Pence, 2006; Dagher and Sun, 2016; Bongaerts et al., 2021).

[9] In Florida, foreclosure auctions shall be "advertised once a week for two consecutive weeks in a newspaper of general circulation in the county of the sale", pursuant to Sec. 45.031(2) of the Florida Statute. "The publication of sale shall contain a description of the property to be auctioned".

which any bid is automatically rejected. The credit bid can either be disclosed to bidders or maintained hidden throughout the sale process, but can never exceed the Final Judgement amount. The transaction must be a cash sale and properties are sold "as is".

Traditionally, bidders are required to attend a foreclosure auction in-person during regular business hours on weekdays in a room or at the steps of the courthouse of the county where the property is located. From an economic point of view, this prerequisite involves personal monetary (e.g., transport services, lodging, cost of meals and tips, etc.) and non-monetary (e.g., time spent) costs bidders must incur to participate. This barrier arguably discourages third-party bidding as well as reduces the amount each bidder is willing to pay. On the court side, traditional live auctions are inefficient because they usually require large resources to handle the sale (e.g., four to five people, rooms) and limit the number of potential bidders who can attend. Bid-rigging or collusion are not unheard of at physical auctions, either.[10]

At the foreclosure auction stage, there are three possible outcomes. In two of those, the auction is considered successful: if any third-party cash bid exceeds the judgement amount, the bank is fully repaid and any surplus balance goes to the defaulting borrower; alternatively, the final bid may be below the final judgement amount and the lenders accept the offer. In this situation, the borrower is still liable for the deficit ("deficiency judgement").[11] Finally, if there is no bid exceeding the lender's reservation price then the auction fails, and the lender becomes the owner of the property which must be then sold as a Real Estate Owned (REO) asset privately. Unsuccessful foreclosure auctions are the most common outcomes in the U.S., with the foreclosing lender buying back the property.[12]

[10]For an example of this serious issue, see here: https://www.justice.gov/opa/pr/nine-real-estate-investors-sentenced-rigging-bids-mississippi-public-foreclosure-auctions

[11]In recourse states, lenders have the option to file a motion for the remaining balance of their debt exposure, but rarely do so (Ghent and Kudlyak, 2011; Burkhart, 2017). In Florida is particularly difficult to do so, as the statute of limitations for deficiency judgment is only one year starting from the foreclosure auction date (Fla. Stat. Ann. § 95.11).

[12]Success rates vary across geographies and over time. For example, ATTOM Data Solutions reports that lenders annually purchased the foreclosed property in more than 80% of auctions in 13 out of 17 years taken into account (2000-16). See https://perma.cc/U8JM-E3XA.

Lenders' business is not to maintain and rehab REO properties. As a result, these assets are more likely to be abandoned and neglected. Not only may the physical conditions deteriorate over time, also legal expenses can accumulate to substantial amounts. For each REO home, lenders are responsible to pay insurance premiums, homeowner's association assessments, property taxes, utilities, and broker reselling fees, which can total up to 16% of the property value (Burkhart, 2017). On top of that, lenders lose mortgage revenue as interest on the loan continues to be unpaid. Since these properties typically remain in the REO state for a long time,[13] these costs can total up to a substantial amount. Hence, a quicker asset disposition at the auction can be considered as the least painful outcome for lenders ex-ante.

2.2 Hypotheses

Auctions are processes to efficiently allocate goods among bidders which, through coordination, competition and social mechanisms, determine a price (Krishna, 2009). Starting in the 1990s, the Internet has allowed different types of auction markets to benefit from advanced technological progress such as low-cost softwares, high-speed communication-infrastructure and client-server architectures. This reduces entry fees and allows to reach a larger audience, even for specialized assets, thereby improving liquidity in these markets (Meyer, 1993; Wyld, 2005). Electronic sales mitigate buyers' frictions due to the convenience of bidding online in the comfort of their own homes or offices. Online auctions run through a browser-based application, without the need for public gatherings. Buyers can save time as well as travel expenses which can instead be used to acquire information about the quality of the property and prepare a more aggressive bidding strategy. Such costs may also be prohibitive in participating. This yields the following predictions:

Prediction 1 *Foreclosure auctions are more likely to be successful when the bidding is conducted electronically.*

[13]Following OCC regulations, REOs should stay in the bank's balance sheet for no more than five years. For a description of this process in greater details, see here: https://www.occ.treas.gov/publications/publicationsby-type/comptrollers-handbook/other-real-estate-owned/pub-ch-oreo.pdf

Prediction 2 *Conditional on auction success, foreclosed properties trade at smaller price discounts when the bidding is conducted electronically.*

Prediction 1 and 2 refer to the marginal effect of online bidding compared to physical bidding, and are related to the intensive and extensive margin effects of auction participation. Lower transaction costs may permit marginal (e.g., who was capacity or financially constrained) bidders to break-even and participate. Regardless, this reduction of trade costs positively affects bidder's reservation price and, thereby increasing competition. The reason is that investors care about after-cost returns and hence can bid more, even if markets in both cases are equally competitive. Moreover, savings in bidding cost and time can be used to prepare a better bidding strategy and acquire more information about a specific property. In conclusion, predictions 1 and 2 may follow from either higher participation, or from more aggressive bidding.

2.3 Empirical Strategy

Foreclosure auctions offer a good setting for empirical identification of electronic means of purchase as the sale environment is subject to regulated rules of court supervision. There are no negotiation frictions between agents, user experience does not play a role,[14] and sellers have limited or no influence on the outcome.[15]

One could estimate the effect of online bidding technology on auction outcomes by comparing real estate foreclosures in states with electronic bidding to other states that use live bid outcry auctions. However, such an estimation strategy would likely be biased as different foreclosure laws may apply, mortgage markets differ, and properties may have non-comparable characteristics. To address these issues, I focus on a single state and exploit the staggered implementation of a Florida's 2008 law across counties.

[14]Uncertainty about product quality in online environments may influences buyer's expected utility and reservation price negatively (Fung and Lee, 1999). However, judicial statutes in the U.S. forbid to inspect the house before the foreclosure auction takes place, regardless of the sale method.

[15]Due to property deterioration, management and legal costs, lenders have incentives to proportionally set their credit (reservation) bid and sell foreclosed properties in cash at the auction, rather than to rehab and sell them later in the private market. Moreover, as foreclosures are lengthy processes (up to 24 months, Daneshvary et al. (2011)), I focus on a short estimation window to prevent any selection issues.

Florida rank in the top 5 U.S. states hardest hit by mortgage foreclosures during the Great Financial Crisis. As in any other U.S. judicial states, clerks of Florida courts have traditionally conducted foreclosure sales by in-person auctions. While facing a foreclosure wave that was engulfing the state, in June 2008 the Governor of Florida approved House Bill 773 to permit judicial sales of real or personal properties to be conducted by electronic means. When a county switches to online bidding, bidder deposits, bid offers and any sale related payments can be handled electronically, reducing the need to physically go to the courthouse.

Importantly, the proposed technology was not mandatory. County courts took up the policy at different points in time (see Figure 1). In the first ten years, 29 out of 67 counties adopted this electronic bidding technology. All adopters (except for Palm Beach) started using *realauction.com*, a private online auction platform.[16] Since a few counties never adopted, identification of the treatment effect comes from *whether* and *when* treatment ever occurs. This staggered adoption allows to compare foreclosed properties in electronic bidding counties ("treated") to those that did not adopted the technology change ("control") among the set of contiguous counties over a 3 years time window in a Difference-in-Differences (DiD) design. This matching strategy is based on relatively small geographical areas to ensure that real estate assets are exposed to similar economic conditions.

The staggered DiD is a quasi-experimental technique that addresses potential divergences in market conditions and contemporaneous laws. To circumvent the heterogeneity problems and negative aggregation weights of the two-way fixed-effects DiD estimator with staggered treatment (Goodman-Bacon, 2021), I follow Cengiz et al. (2019) "stacking" methodology and ensure that the set of controls associated with a treated unit are always "never-treated" during the sample window under consideration (i.e., 36 months). This method produces event-specific datasets that are then stacked in event-relative time. The stacking process consists of grouping treated counties with both their "never-treated" counties and (if any) "late-treated" counties

[16]The fact that the auction bidding format is not a seller's decision helps in establishing that the electronic technology is an exogenous treatment. This allows to study the effect of the electronic bidding on foreclosure outcomes.

among the set of neighboring ones.[17]

To ensure there is always exactly one treated unit and at least one control county within a border cohort, I exclude treated counties that are surrounded only by other treated counties (there are three such cases). The matching procedure (with replacement) makes this DiD functional form equivalent to a setting where the events happen contemporaneously (Baker et al., 2021). As foreclosures are rather lengthy processes, our estimation window is short enough to mitigate selection bias of new properties entering foreclosure.[18]

The DiD regression equation takes the following form:

$$FclOutcome_{i,c,t,cb} = \beta Treated_{c,b} \times Post_{t,cb} + \gamma Treated_{c,b} + \eta X_{i,c,t,cb} + \nu_{cb \times t} + \alpha_n + \varepsilon_{i,c,t,cb} \tag{1}$$

where $FclOutcome_{i,c,t,cb}$ is the outcome of a foreclosure auction (or REO sale) of property i located in county c at month t. In the two baseline models, the dependent variables are either auction success or property discount. For each county border cohort cb, the $Treated_{c,b}$ vector takes value 1 if a county c receives the technology treatment, and 0 otherwise. $Post_{t,cb}$ is a dummy variable taking value 1 in all months t after a county c in a group cb receives the treatment, and 0 before that. The standalone $Post_{t,cb}$ coefficient is absorbed by time fixed effects. The vector of residential property characteristics is denoted by $X_{i,c,t,cb}$, and includes property age, size (total area of all floors), number of residential units, and appraised structure quality. Finally, $\nu_{cb \times t}$ and α_n are two sets of fixed effects at county border-by-month level, and at census tract n level, respectively.[19] The stacked cohort (county border) fixed effects are crucial for this specific DiD design and are the only features that differ from

[17]Among the set of never-treated counties, Franklin, Taylor, Dixie, Lafayette, Suwannee, Hamilton, and Madison do not share a border with any treated county and, thus, are excluded from the analysis.

[18]Lenders' anticipation concerns are most likely to arise when they have control over the sale process. However, creditors have limited influence on the sale process during a foreclosure auction, as the property is not yet in their possession. Moreover, it is not in their interest to overbid the judgement amount when borrowers are underwater (90% of the cases in the auction platform sample).

[19]Census tracts are small geographic area in the U.S. with a population of approximately 2,000-4,000 persons.

the standard DiD estimand procedure.[20] Standard errors are clustered at border-by-county (policy) level which account for the possibility that auction outcomes may be correlated within a county, as well as for the expanded data structure. Conditional on the parallel trend assumption being satisfied, the coefficient β on the interaction term $Treated_{c,b} \times Post_{t,cb}$ captures the effect of the introduction of the online bidding technology.

3 Data

To study foreclosure outcomes one should observe the characteristics and location of foreclosed properties, as well as auction success and transaction prices. I use comprehensive data from Florida Department of Revenue to accomplish this task. For tax purposes, this state agency collects annual assessment rolls of real properties in all Florida's counties. Assessment rolls are publicly available and include information on each parcel, such as the owner's name and, place of residence, property characteristics, as well as its assessed market value. By law, members of the Property Appraiser's Office should inspect the exterior of a property in a given county at most once every five years. Although in my sample property inspections occur every 3.5 years on average, the assessed value is calculated on an annual basis due to assessors' interpolating calculations.

The price, date and, most importantly, the type of at most two property transfers per year are reported in the assessment rolls. Unfortunately, the transfer codes are not precise enough to distinguish a foreclosure auction sale (third-party acquisition) from an REO sale. However, a simple and well-founded classification rule for auction success exists: property assessors also record transfers and prices when auctioned properties go back to lenders (Anenberg and Kung, 2014; Chinloy et al., 2017). Although these are bookkeeping entries with no money changing ends, researchers can use them to identify auction outcomes. I classify a third-party auction sale if a "dis-

[20]For instance, one county border cohort in the main sample is composed of: Orange (treated county), Lake, Seminole, Brevard, and Osceola (untreated counties).

qualified" transfer in month t is not followed by any other "disqualified" transfers in the subsequent four years, and if a bank is involved in the sale. The results are robust to alternative choices of this time window.[21] I use the actual auction outcomes from the official online platform that handles counties' foreclosure auctions to validate this strategy. Eventually, this simple approach yields a relatively low (i.e., 10%) false positive-negative rate for the post-treatment sample.

I focus on single-family residential properties with at least one disqualified sale over the entire sample period. In the price analysis, I follow Donner (2020) and exclude observations with transaction prices that deviate by more than 50% from their appraised values to mitigate manual entry mistakes. Unfortunately, the details of debt features (e.g., lender name, debt outstanding, default date, etc.) are not observable in the data. This would be an issue for identification in case any changes in lenders' incentives to foreclose or to accept bids before and after the technology shock materialize immediately. This is unlikely to be a persistent bias in such a short estimation window, as foreclosures are structured and lengthy processes.[22] Regarding lenders' behavior at the auction, there is no reason why lenders should reject good bids, as REO assets are very costly to maintain and recourse clauses are rarely used. Therefore the likelihood that lenders anticipate and manipulate foreclosed auctions in this context is rather small.[23]

Table 1 shows the summary statistics of the variables used in this study. Panel A shows that lenders manage to sell to third-party bidders 18% of their foreclosure auctions. The average discount of an auction sale is slightly less than 8%. This is in line with existing quality-adjusted estimates of the foreclosure discount in the literature

[21] "Disqualified" sale transfers with qualification codes "transfer of ownership in which no documentary stamps were paid" or "transfer to or from financial institutions (including private lenders)" are included.

[22]. Moreover, a robustness check confirms that the effect of electronic bidding does not depend on the type (private or public) of foreclosing lender.

[23] Note that an auction may be rescheduled by lenders. Once they know that bidding improves, sellers may engage in canceling some of their scheduled auctions. However, this is unlikely to be the case in Florida, as in 2010 the Florida Supreme Court approved an amendment to the Florida Rules of Civil Procedure (Form 1.996(b)), increasing frictions in case a foreclosing plaintiff wishes to cancel and reschedule a mortgage foreclosure sale (https://www.jimersonfirm.com/blog/2020/10/cancel-reschedule-mortgage-foreclosure-sale/).

(Clauretie and Daneshvary, 2009; Chinloy et al., 2017; Donner, 2020). The average auctioned house is 27 years old, has 1820 (=exp(7.507)) square feet of total living area, has no detached parent/grandparent suite, and has an overall appraised quality of the predominate structure slightly above the "average" rating (3). Though unsuccessful auctions sell later as REO properties at about half of the auction discount, lenders do incur additional holding costs when selling an REO home, as described above.

[Table 1 here]

Panel B shows the changes in auction outcomes and in the property characteristics before and after the electronic bidding shock. As expected, there are considerable variations in the variables across counties and over time. Comparing treated and control counties, we can already intuitively see the effect of the policy: treated counties improve from an average auction success of 14.47% to 19.58%, while the success probability in control counties stay relatively constant over time (19.16% and 19.05%). A similar trend can be observed by looking at the discount of successfully auctioned properties. In the pre-event window, the average values of both dependent variables statistically differ between groups. This could reflect the heterogeneity of the real estate market in a vast state such as Florida. Alternatively, it is the endogenous part of the policy implementation, an issue formally mitigated in the parallel trend test and in the instrumental variable exercise. When it comes to property characteristics, such as house age, size and quality, the average values of the treated group and the control group differ from each other, emphasizing the need to control for these characteristics in a property-level regression.

4 Results

4.1 Foreclosure auction success

The analysis starts with a visual inspection on the dynamics of the main dependent variables of interest. Figure 2 focuses on neighboring counties and compares the monthly success rate of foreclosure auctions, defined as the fraction of third-party auction sales to the total number of auctions. For each month, values of treated counties (blue line) and of control counties (red line) are averaged and then plotted over a 36-month window around the technology adoption date ($t = 0$). The shaded area around each solid line represents the 95% confidence interval. To avoid an unbalanced number of counties between the two time windows, border cohorts with a pre-policy window shorter than 15 months are excluded from this graph.

[Figure 2 here]

Before the treatment date ($t < 0$), both lines have a decreasing trend. This may be due to the foreclosure-engulfed period surrounding the timing of most adoptions. Nevertheless, the fact that both lines move in the same direction mitigates (at least in part) any concerns about endogenous policy incidence. At $t = 0$, treated auctions start to become more successful, as the blue line jumps and reaches the red line. After a 5-6 months of overlap, when the technology may only have been adopted by more prosperous and more risk-oriented investors, the blue line starts to overcome the red line. While this graph only provides a crude description of the dynamics in the auction success rate, it highlights the potential for electronic bidding to have a significant impact on foreclosure auction success.

Table 2 presents a more formal test of hypothesis 1 by means of OLS regressions. The coefficients are estimated with a linear probability model (LPM) and follow the regression model of equation (1). All specifications include county border-times-month fixed effects, which also capture the direct effect of the $Post_t$ dummy and hence make it redundant on its own. Column 1 shows that the dependent variable $AucSucc_{i,c,t}$ is positively affected by the electronic bidding technology. The DiD interaction coefficient $Treated_c \times Post_t$ equals 0.0542, and statistically differs from zero. In column 2, characteristics of the auctioned property are added as the control variables. The signs of the control coefficients are consistent with the view that, when sellers have limited pricing power, asset illiquidity impairs trade, as older and larger houses are less likely to be sold to third party buyers. Yet, importantly, the interaction term estimate is barely affected. The fact that the results are not driven by the inclusion of controls suggests that the treatment does not have strong heterogeneous impacts across sample subgroups (Baker et al., 2021). Column 3 mantains the same structure of the specification with controls, and adds county fixed effects to the model to control for county differences within a border group. The main coefficient of interest decreases only slightly in magnitude. Finally column 4 and 5 add property zip code and census tract fixed effects, respectively, and in either case the interaction coefficient remains statistically and economically significant. When compared to the unconditional mean of auction success, the estimated economic effect of electronic bidding is relatively large (27%).

[Table 2 here]

The time breakdown of the point estimate constitutes a crucial part of any DiD analysis. Figure 3 plots the coefficients and their standard errors of the interaction term of the last column presented in Table 2 in an event-study design. The $Post_t$ dummy is unpacked into several time indicators that "switch on" only during a short window of reference. To avoid multicollinearity, the omitted coefficient is the time dummy $t \in (-5, 0)$ that equals to one just before a county technology adoption ($t = 0$).

[Figure 3 here]

Before the treatment date (dotted vertical line), point estimates are indistinguishable from zero, which confirms that the "parallel trend" assumption is satisfied. The comparable dynamics between the two groups in the pre-treatment period points largely in favor of the conditional independence condition. Indeed, the point estimate becomes positive and significant just after the policy implementation, confirming the idea that the legal structure of the foreclosure process does not admit leakages in the pre-shock period. One explanation for the negative (but not statistically significant) pre-trend may be that the policy adoption depends on poor foreclosure outcomes. In section 4.3, I use an instrumental variable to mitigate such concerns.

4.2 Foreclosure auction discount

The extensive margin effect of electronic bidding is an important result. As table 2 has presented, third-party bidders are more likely to buy an auctioned property because of the electronic sale method. Higher auction success rate means that there are fewer REO assets loading banks' balance sheets and degrading a neighborhood conditions. Another important question to investigate is what happens to the final price of third-party acquired properties (an intensive margin result). It could be that the shock just make lenders willing to sell more of their foreclosed properties but at the cost of lower prices. Instead, if lender incentives do not change and more (possibly high-valuation) buyers join the market, competition on the bidding side should increase final prices. In Figure 4 the dynamic trend of the average foreclosure discount among successful auctions is presented. The graph shows a comparison between treated and control counties around the treatment date.

[Figure 4 here]

Average values are noisy but both groups seem to move in parallel in the period before the policy adoption. At $t = 0$, the average discount in treated counties drops more than in similar control counties. The exercise in Table 3 tests this observation more formally, regressing the auction acquired property discount on the policy dummies and house characteristics.

[Table 3 here]

The dependent variable is $AucDisc_{i,c,t}$ which is defined as one minus the fraction between the final price (winning bid) and the market value of the property assessed a few months before the sale by county appraisers. Larger values of $AucDisc_{i,c,t}$ mean lower final prices. In column 1, the coefficient on the interaction term is negative and statistically significant. This is consistent with Prediction 2. Property characteristics are included into specification of column 2, and the interaction coefficient remains statistically significant and negative. In column 3, 4, and 5, geography fixed effects are added to the model. Even with the most stringent fixed effect structure (at the census tract level in column 5), the coefficient on $Treated_t \times Post_t$ is negative and stabilizes at 3.37%. This means that the electronic bidding technology reduces the auction foreclosure discount by slightly more than 3 percentage points. Therefore, also at the intensive margins, electronic bidding improves foreclosure auctions, as the discount lenders receive shrink substantially (42% of the average discount). This is important for borrowers whose properties are foreclosed, as they are subject to smaller deficiency judgements. Moreover, these results may have implications for non-foreclosed properties as well, due to lower negative (marked-to-market) price spillovers. Note that for the welfare analysis that will appear towards the end, pricing effects will not show up as these are zero-sum transfers.

Figure 5 presents an event study graph, similar to Figure 3, but for price discounts. Here we can see that the parallel trend assumption is not violated (coefficients statistically insignificant for $t < 0$), and that the effect is not immediate which is consistent with technology adoption lags.

[Figure 5 here]

4.3 Instrumental variable approach

One econometric issue that may complicate the estimation of treatment effects is when a group selects into treatment precisely to affect the outcome targeted by a policy. One solution is to control for the forces driving treatment, by modeling them as a function of the pre-treatment county characteristics. These pre-treatment characteristics can then be used as instruments to identify the treatment incidence (Besley and Case, 2000). In particular, the OLS estimates may inflate the true effect given that switching to electronic auctions may happen when foreclosure success is low and discounts are high.

I exploit (non-)foreclosure legal filings a court receives to predict its technology adoption decision. The idea is that when the number of non-foreclosure filings f (or more generally workload) courts foresee becomes large enough, it is more convenient to decentralize some operations and switch to online auctions. Let us assume that the total annual cost of running auctions is the sum of a fixed and a variable component. Suppose in the onsite case, auctions have no fixed costs (courthouse already built) and a marginal cost for manpower equal to C. On the other hand, an online auction can be conducted at no marginal cost because it is decentralized and operated automatically, conditional on paying an annual fixed fee P to the platform. Then, a workload level f^* exists beyond which it is convenient to adopt the electronic technology: $Cf > P$, or $f^* > P/C$. The exclusion condition is likely to be satisfied as the number of incoming civil filings (e.g., tort actions, contract disputes, products liability issues, malpractice matters, infringements of intellectual property) in a month are unlikely to affect the outcome of foreclosure auctions in previous months.

Data on the number of monthly cases filed per courthouse are sourced from the website of the Office of the State Courts Administrator. This service collects court-related data of all 67 county courts in Florida. For each county, real property cases filed in a month are retrieved from the Trial Court Statistics database, and averaged across a short (e.g., 18, 12 or 6 months) time window before the group treatment date. Figure 6 plots the incoming legal filings, in logarithmic terms, against group adoption timing (months passed since the policy date, i.e. June 2008). The different panels refer to foreclosure cases (panel A) and non-foreclosure cases (panel B). Each county border group has a different colour and lies on a vertical line.

[Figure 6 here]

First, treated counties (triangle) are on average more exposed to both foreclosure and non-foreclosure legal filings than control counties (circles). This can be seen from the fact that triangles are typically at the top of these graphs. In other words, expected workload seems to be a good predictor of the technology take-up. Also, treated and control units of late adopters (larger values on x-axis) face fewer backlog on average. This path is consistent with the fact that late adoptions were far from the 2008-2010 financial crisis. Table 4 shows the results of the instrumental variable estimation. The bottom panel presents the first stage coefficients. In the same spirit of the Duflo (2001) methodology, interaction terms between $Post_t$ and foreclosure ($Fcl_{c,t\in(-12.0)}$) cases or non-foreclosure cases ($NonFcl_{c,t\in(-12.0)}$), averaged over the year before the treatment date, instrument the endogenous $Treated_c \times Post_t$.[24]

[Table 4 here]

As expected, the coefficients in the first stage are positive and statistically significant, suggesting that more exposed counties within a border group are more likely to adopt the policy (bottom panel). In both the auction success model (column 1 and 2) and the auction discount model (3 and 4), the filings variables pass the weak

[24] I find 2SLS results to be robust to different time windows over which legal filings are averaged.

instruments test, as proven by the Kleibergen-Paap rk Wald F-statistic. Moreover, the coefficients of the second stage (top panel) are in line with predictions 1 and 2. Following the electronic bidding technology, auction success increases and auction discount shrinks. In terms of economic significance, the 2SLS estimates are about twice the OLS coefficients of the baseline model (the last columns of table 2 and of table 3). [25] Larger current backlog predicts more future foreclosures, which hamper auction success and amplifies price discounts through a supply effect. This channel may not be captured by the OLS estimates. Importantly, the fact that 2SLS estimates are larger than OLS ones alleviates concerns about endogenous adoption. Whereas with endogenous adoption the baseline OLS results would have been upward biased (due to potential bouncing effects), the IV shows that, if anything, the baseline results are downward biased.

4.4 Additional results

This section goes beyond analyzing the effect of digital auction adoption on auction success and price. In the next set of exercises, I identify the nature of the effect by exploiting information on the identity of auction participants, as well as characteristics of courthouses and foreclosed properties. But first, I subject the benchmark model to some robustness exercises, and explore alternative explanations for increased liquidity.

4.4.1 Robustness Tests

This section tests the robustness of the auction baseline inferences. First, to ensure that the estimation process is not capturing any size effect of treated counties, column 1 of Table 5 maintains the same structure of the last column of Table 2. This placebo exercise drops auction observation from the actual treated county in each border group, and assigns treatment to the control county most similar to the treated one in terms of population. County border cohorts with only one control county are not

[25]It is important to notice that the IV estimate is only 1.5-2 times larger than the OLS estimate, suggesting that the instrument is not weak and that the OLS estimate slightly understates the true effect (Jiang, 2017).

part of the sample in this exercise.

[Table 5 here]

In this case, the interaction term coefficient is almost zero and it is not statistically significant. Although the parallel trend assumption is inherently untestable in any DiD estimation, this placebo exercises confirms that the control group did not experienced any change in outcome.

In column 2 I formally address an increased "awareness" hypothesis. Electronic bidding may have positive effects on foreclosure auctions because people may suddenly realize the existence of these markets. By focusing only on foreclosed properties in control counties that are very close (5 miles) to the border, we can study whether any positive "awareness" spillovers is present. The $Post_t$ dummy is not statistically significant, which mitigates this concern. Similarly, to exclude the possibility that treated counties are affected by their neighbors (e.g., buyers of control areas may get attracted from treated regions), column 3 excludes properties in both groups located close ($\leq$ 5 miles) to the county border. In this case, although the matching comparability might be loosened, we can see that the interaction effect is positive and similar to the baseline result. Column 4 excludes border cohorts with counties that received the treatment just before 2010. These have mechanically a shorter pre-shock window since the data starts in 2009. The results are similar to the baseline. Next, the sample in column 5 checks whether estimation is contaminated by comparisons of late versus earlier treated counties, and whether there are systematic differences in the effect across early and late adopters. This does not seem to be an issue, as the main coefficient of interest remains positive and statistically significant. Column 6 estimates the coefficients by means of Weighted Least Squares (WLS) with weights equal to the inverse of the number of counties in each border group, and the baseline results are confirmed. Finally, column 7 tests whether incentives from supply (lender) side play a confounding role. The triple interaction between the electronic bidding effect and an indicator for Government Agency (including HUD, Fannie Mae, and Freddie Mac) loans is not statistically significant, confirming that over such a short estimation window the foreclosure process is difficult to manipulate.

4.4.2 Auction Buyers

To further the understanding of the source of frictions and how welfare gains redistribute, it is important to study types of auction buyers. Therefore, I examine how the composition of auction buyer pool changes as a result of the new auction bidding technology. Real property roll data contains information at property-level about the name and residence (up to the zip code) of the owner. This panel comprises the universe of residential properties in Florida. For each acquired property, I match the name of a buyer at foreclosure auction with sample of owners of non-foreclosed properties in the previous year to identify her starting residence place and real estate portfolio volume. To minimize the case in which different persons have the same name, I exclude owners with multiple residences in a year.[26]

[Table 6 here]

Table 6 presents the results of the DiD regression on auction buyers' characteristics keeping the same structure as the baseline specification in the last column of Table 2. In column 1 the dependent variable is a dummy variable taking value 1 if the buyer was resident in a state different from Florida in the prior year, and zero otherwise. In this regression, the interaction term coefficient capturing electronic bidding is negative and statistically significant. This suggests that out-of-state buyers are less likely to buy foreclosure auctions when the bidding is made online. Local buyers may be more informed about the market and bid closely to the real value, while outsiders may

[26] This matching procedure is imperfect for two reasons: first, the database reports only the ultimate owner, and not the household composition. Therefore, any person who is married with an owner and buys a foreclosure auction in $t+1$ will not be captured. Second, owner names may not be matched because of typos or additional co-owners. All such cases cannot be part of the analysis as are not observable. Therefore, resulting sample for this analysis is reduced.

fear a winner's curse. This evidence is confirmed in the next two columns, where the dependent variables become the distance (in thousand miles) between final auction buyer b and property i, and between final auction buyer b and courthouse in county c, respectively. In both cases, the interaction coefficient is negative. Therefore, the electronic bidding technology has unlocked access to local buyers, who probably are those with more information about the (local) market. The new technology allows them to bid more precisely and acquire a foreclosed property at the auction.

Next, column 4 considers the role of buyer type which captures capacity and financial constraint dimensions. The $Professional_{i,c,t}$ dummy takes value 1 if the auction buyer is an institutional investor, and zero otherwise.[27] The DiD interaction term receives a negative coefficient that is statistically significant. Similarly, column 5 proposes the effect of electronic bidding on the buyer composition in terms of portfolio size. The dependent variable takes value 1 if the auction buyer owned more than one (non-foreclosed) property in year t-1. Also in this case the interaction coefficient is statistically significant and negative. Taken together, these results suggests that easier access to the bidding process reduces professional and institutional active participation. Increasing competition at the bidding pushes up the price and a foreclosed property becomes simply not an attractive investment opportunity anymore. Finally, column 6 shows that buyers of electronic auctions become owner-occupant as they hold on to the property as the main residence and flip it less often in subsequent years. Since the asset holding period proxies for high-valuation of the asset itself, this suggests online auctions are more likely to locate the "right" holder.

4.4.3 Channels

In this section, I explore the channels driving the positive effects of electronic bidding. The purpose here is to get at deeper causes of baseline results by separating a market access channel (more operational) from a capacity and funding constraint. Taking

[27] Unfortunately tax appraisers do not collect information on the legal status of the property owner. Therefore, I perform a textual analysis on the owner name variable and look for terms resembling banks or real property companies, such as "bank", "enterprise", "mortgage", "corporation", "credit", "trading", "international", "group", etc.

the specification in the last column of Table 2, the regression coefficients displayed in Table 7 include triple interaction terms of the treatment, the timing dummy, and one channel at a time. All regressions include cross-interaction terms between the channel, treatment and time variable (not displayed for brevity).

[Table 7 here]

Column 1 and 2 investigates the role of commuting costs a potential bidder must incur to reach the courthouse. I calculate a court remoteness index as one minus the fraction between the population in the zip code of the court and the total population of the county. Larger values of $Remote_c$ imply that the court is located in one of the most remote cities in the region and that is not easily reachable by a large audience. We see that the interaction term between the electronic bidding and the remote index obtains a positive and statistically significant coefficient. A similar picture emerges in column 2, where the triple interaction coefficient includes the distance (in thousand miles) between the foreclosed property and the court. When bidders have to commute to the courthouse for an auction, the set of properties more distant from the courthouse are disadvantaged because it is more costly for highest valuation users (those who already live close to the property) to participate. Therefore, online auctions may benefit more the properties for which their high-valuation buyers needed to commute the most. In line with this argument, the estimate in column 2 is statistically significant and positive. Overall, these results show larger gains of electronic bidding in situations where the marketplace has more difficult accessibility.

Column 3 seeks to understand whether the electronic bidding effect could relieve fire sales. This time the triple interaction includes the number of foreclosure auctions a county experience in a given month. The prediction is that the success of an auction is negatively related to the supply of contemporaneous foreclosures (absorbed anyway by time fixed effects in the baseline regressions). The positive and statistically significant coefficient on the triple interaction term suggests that larger trade gains are found in more competitive periods of time. The electronic platform attracts more buyers aggregating and distributing liquidity among properties. This suggests that electronic auctions are useful in relaxing capacity constraints. Finally, column 4 tests matching allocation. Good quality assets are easier to sell, but trade frictions (such as remote marketplace) in a physical bidding process might have restricted the pool of buyers. The results suggest that the impact of the electronic bidding on auction success increases in the overall quality of the predominate structure(s) on the property. In particular, the interaction of the triple interaction is positive and statistically significant. Unfortunately, the effect on the number of bidders cannot directly be tested since data for in-person auction bids is unavailable. Nevertheless, this evidence is consistent with new bidders with different preferences (e.g., ready-made assets) joining the bidding process. The analysis on various channels is in favour of operational access costs, as local people who are better able to evaluate the value of the house may not find it easy to go to in-person auctions (e.g., lack of information about the auction, time costs, etc.).

4.4.4 REO sales

When a foreclosure auction does not succeed, the foreclosed property enters into the bank's balance sheet as Real Estate Owned (REO) asset, which must be sold later on privately by the bank. For an accurate welfare analysis, it is important to track and analyse these asset sales.[28] Higher auction success leaves fewer REOs in a market. But do these leftover REOs trade at lower prices? REOs can suffer from a "stigma" effect (Harding et al., 2012). If auctions become more successful, the stigma associated with troubled REO assets could be even amplified in principle. Table 8 explores this question by means of OLS regressions and survival analyses.

[Table 8 here]

[28]From a societal perspective, asset resales post-auction cannot guarantee efficient allocations (Krishna, 2009). In resales there are typically transaction costs, and bargaining delays. Inefficiencies arise also from the fact that resale prospects may distort rational buyers' incentives at auction.

Specifications in Table 8 share the same specification structure of the baseline model presented in Table 3. Column 1 shows that the electronic bidding effect on REO foreclosure discount is positive and statistically significant. The estimate equals 1.48%, which is less than half of the positive effect on auction discounts. If at first sight this result may counteract higher auction success, one should also consider transaction costs associated with REOs that make the results on auction discount even more prominent to get a full picture. Moreover, one possibility is that some REO assets are quite different in terms of characteristics with respect to successful auctions and could simply have a minimal probability of success. Therefore, in column 2, I exclude from the sample REO properties that receive a low predicted score (below 10th percentile) from a regression with auction success as the dependent variable (last column of Table 2). Here the interaction coefficient loses statistical significance, highlighting the fact that REOs do not worsen and do not offset lower auction discounts. In column 3 and 4 I study the electronic bidding effect on REO buyers. Even though there is no effect on the distance, buyer type is affected. The coefficient on the interaction term in column 4 is positive and statistically significant. A potential interpretation is that professional buyers are crowded out from auction markets and stitch to the REO market, where potential profit might still be present and other ways of financing are possible.

As the REO effect potentially offsets the auction effect, I study the net effect from an aggregate perspective. The last two columns of Table 8 investigates the time on market of properties entering foreclosures. The dependent variable is the time elapsed from the auction date to the REO actual sale date and comes in the form of months. In these cases I estimate the coefficients on the full (i.e., auction and REO sales) sample with duration models, as using regression techniques involves estimation problems (i.e., the dependent variables are affected with the passing of time). Column 5 estimates a Cox proportional hazards model via maximum likelihood. The disadvantage is that this type of estimation may have issues to fit a high dimensional fixed effects model. Therefore, in column 6 I use a multilevel mixed-effects parametric survival-time model, with conditional distribution of the response given random effects given by a Weibull distribution. In both cases, the coefficient on the interaction term is positive and statistically significant. According to both estimations, the hazard increases (covariate negatively associated with length of survival) as a result of the electronic auction bidding. Overall, this suggests that lenders manage to sell foreclosures quicker.

4.4.5 Ex-ante Credit

The loss given default is an important driver of investment decisions. In the mortgage setting, the costs lenders expect to bear at the foreclosure stage can have direct implications for the supply of new credit (Pence, 2006; Dagher and Sun, 2016; Bongaerts et al., 2021). This section studies the direct implications electronic bidding has on lending using data on mortgage applications from the Home Mortgage Disclosure Act (HMDA). The regression takes the form:

$$Accept_{i,c,t,cb} = \beta Treated_c \times Post_t + \gamma Treated_c + X_{i,c,t} + \nu_{cb \times t} + \alpha n + \varepsilon_{i,c,t,cb} \quad (2)$$

where the dummy variable $Accept_{i,c,t}$ takes the value of 1 in case a mortgage application i for a house in county c in year t is accepted by the bank, and zero otherwise. The policy variables $Treated_c$ follows the same definitions of the auction-level regressions; given that HMDA collects data on an annual basis, $Post_t$ switches to one for those county borders in which treatment occurs before June (otherwise equals to one from the subsequent year onwards). The linear probability model controls for borrower characteristics $X_{i,c,t}$ such as gender, race, income, Debt-to-income ratio, co-borrower presence, and a *jumbo* indicator.[29] Moreover, to maintain a structure identical to the auction-level equation (Eq. 1) county border-times-year fixed effects, $\nu_{cb \times t}$, and census tract, αn, fixed effects are included. The sample differs across county border groups and it is centered around the treatment year. The results of the stacked DiD estimation is presented in Table 9.

[29]In the U.S. mortgage market context, lenders have the option to transfer the credit risk of a loan they grant by selling (securitizing) it to Government-Sponsored Enterprises (GSEs)..

[Table 9 here]

Column 1 studies lender acceptance decisions with the set of borrower controls. It shows that the interaction coefficient of interest is positive and statistically significant, suggesting that lenders are inclined to extend more credit once they expect a lower foreclosure or delinquency costs. Moreover, the effects are economically meaningful, as the electronic bidding shock is associated with an increase of 0.78 (=.00565/.7229) percentage points in acceptance rates. Figure 7 shows the point estimates of the DiD coefficient in an event-study fashion. We can see that before treatment (*t=0*), the effect is indistinguishable from zero. At t=0, it jumps to a positive value (i.e., around 0.005) and stabilizes afterwards.

The next column explores whether the incorporation of future foreclosure payoffs differs by borrower default risk. Unfortunately, lenders do not report borrower's FICO scores in HMDA during my study period. Therefore, I use a proxy variable, $Risky_{i,c,t}$, which is a dummy that takes value one if the borrower's DTI ratio is higher than the county c average in that year t, and zero otherwise. We can see that the triple interaction is statistically significant and positive, suggesting that the improvement in foreclosures benefits marginal borrowers who were possibly excluded from credit markets before.

Column 3 exploits non-foreclosure caseloads to predict technology adoption by means of an instrumental variable approach that is similar to the one presented in the auction analysis (section 4.3). The 2SLS estimates with non-foreclosure workload (column 3) show that the DiD interaction coefficient remains statistically significant and even increases in magnitude by a factor of 4 (economic significance is 2.77%=.02/.72).[30]

Next, I study the effect that better foreclosure payoffs have on mortgage pricing decisions. Lenders in HMDA are required to report interest rates only if these are higher than comparable Treasury rates. In column 4, I change the dependent variable to $HPrice_{i,c,t}$, a dummy equals to one if the interest rate on the mortgage loan

[30]The results are qualitatively similar when using foreclosure caseload as an instrument.

origination is reported. The DiD coefficient is negative and statistically significant, suggesting that lenders start charging lower interest rates in areas with electronic foreclosures. This evidence suggests there are substantial ex-ante pricing effects of lower foreclosure costs.

Finally, the last two columns zooms into lender's behavior when a borrower defaults. Using loan performance data from the Freddie Mac's Single Family Loan-Level (SFLL) dataset, I retain defaulting mortgages around the treatment dates of treated Florida counties. A $Modify_{i,c,t}$ variable is regressed on various loan characteristics such as loan age (in months), Loan-to-Value ratio, Debt-to-Income ratio, and the borrower FICO score.[31] Loans from contiguous 3-digit zip codes in Georgia (for Nassau and Leon) and in Alabama (for Walton and Okaloosa-St.Rosa-Escambia) are used as control units. Either a Cox proportional hazard model (column 5) and a multilevel mixed-effects parametric survival-time model (column 6) fails to reject the null hypothesis of no change in modification behavior. Nevertheless, these results should be interpreted with caution given that lenders may have little power in terms of loss mitigation decisions for the sample of loans utilized.

4.5 Welfare

The measurement of welfare is centrally important to the economic analysis of policies. In this case, we have seen that the policy about technology adoption has improved the auction stage of residential foreclosures in Florida. Without taking into account secondary effects (e.g., deficiency judgements, court staff costs, and other externalities) for simplicity, the surplus is primarily generated through faster allocation of assets away from imperfect users (lenders) and assigned to high-valualuation users (third-party buyers). Note that higher auction prices themselves (section 4.2) are not

[31] Unfortunately, the property location is reported only up to the 3-digit zip code in the SFLL data set. The overlap between those areas and counties is far from perfect. However, since 3-digit zip codes cannot span two distinct states, I focus on four areas closer to the Florida borders for identification: Nassau (320xx), Leon (323xx), Walton (324xx) and Okaloosa-St.Rosa-Escambia (325xx). Note that zip code 325xx spans three counties: Okaloosa, St. Rosa and Escambia. They are grouped together, and are assumed to receive treatment on the March 2010, which is between treatment dates of Okaloosa (January 2010) and Escambia (June 2010), but long time before St. Rosa (February 2010).

a welfare gain as this is just a transfer from one party to the other.

The welfare calculation borrows statistics from other data sources about Florida and considers 2015 as the reference year. There are 55,000 foreclosures every year.[32] In the data used in this paper, the average time on the market for REOs is 7.5 months. The results of 2 imply that electronic bidding has decreased the number of REOs by **5%**. The welfare effect of the electronic bidding can be split into three components: opportunity cost, intermediation, and regulation.

1. Opportunity costs (empty homes): the first part of the welfare calculation concerns the value generated by putting the asset in its best use. Houses that become REOs cannot be rented, which is a deadweight loss.[33] The average monthly rent of a two bedroom apartment is \$947 (www.rentdata.org). The monthly value is: $\mathbf{5\%} \times 55,000 \times \$947/12 months = \$217,000$

2. Effort in vain (Brokerage fees): REOs are costly to maintain. The main post-auction expenses lenders have to pay can total up to 15.95%.[34] These include (i) maintenance expenses, (ii) tax and insurance on the property and (iii) reselling brokerage fees. From a social welfare perspective, the first two components are "zero sum", as buyers would have to pay for them anyway. The latter is a welfare loss, assuming that realtors' fees correspond to the actual use of resources (i.e., driving, electricity, document stamps, opportunity cost of labor, etc.). Assuming a competitive brokerage market, the selling commission equals the societal welfare costs of the intermediation by the broker. The average real estate commission is 5.5% of the home price (www.realtrends.com). The average price for a two bedroom apartment is \$196,000. Then, the monthly value generated is: $\mathbf{5\%} \times 5.5\% \times 55,000 \times \$196,000/12 months = \$2.5M$

3. Opportunity cost (bank capital): banks need to hold risk capital against defaul-

[32] www.bizjournals.com/orlando/news/2016/10/11/heres-where-florida-ranks-for-most-completed.html

[33] Note that this is likely a lower bound on the consumer surplus of the associated housing utility (if there is an over-supply of properties, the actual associated consumer surplus is higher because the consumer has market power).

[34] See https://www.benefits.va.gov/homeloans/servicers_valeri.asp.

ted mortgages on their balance sheet. This risk capital has an opportunity cost. The welfare costs of capital requirements can be quite large (Van den Heuvel, 2008). The risk-weight on REOs is 100%, or twice the ones on real estate loans in good standing. As the minimum bank equity requirement is 8% of risk-weighted assets, the additional capital banks have to hold to back REOs is 4% (compared to a regular mortgage). Assuming all U.S. banks have some exposure to Florida, and that this capital could have been used in a productive activity such as investing in the stock market at an average annual return of say 8%, the welfare value is: $\mathbf{5\%} \times 55,000 \times 4\% \times \$196,000/12 \times (1 + 8\%/12 months) = \$1.8M$.

Summing up these pieces together, a lower bound for the annual welfare gain associated with this policy is $(\$217,000 + \$2.5M + \$1.8M) \times 7.5 months = \$33.9M$. In perspective with respect to Florida's GDP ($1T a year), over a period of 7.5 months $\$35M$ is roughly 0.56 basis points, which is non-negligible. This can be considered as a lower bound for the welfare calculation as electronic auction bidding likely decreases participation costs (e.g., time, effort, fuel) of third-party bidders and make lenders more willing to extend credit (see section 4.4.5). Moreover, any externalities on parties not directly connected to the foreclosures (e.g., other homeowners in the same neighborhood) are also excluded.

5 Conclusion

Online marketplaces have revolutionized the way parties trade real or financial assets. Arguably, the enabling power of digital markets should matter the most when assets are illiquid, fire sales are costly, and resource misallocation is severe. This study uses such an environment, and investigates the effect of a new technology – electronic bidding – on U.S. mortgage foreclosure outcomes. To empirically answer these questions, I use Florida real property tax roll data together with appraisals of residential properties sold through foreclosure auctions.

Exploiting the staggered electronic bidding adoption of several counties over a 3-year time window, a *stacked* difference-in-differences design estimates an increase of auction success by 27% and a decline on auction discounts of 42%, on average. The results are robust to different samples and placebo tests. Taken together, the welfare improvement is substantial, accounting for around $35M for a state as large as Florida. Other states may benefit from this change in foreclosure process.

An instrumental variable estimation procedure, using court backlog, confirms the effects of electronic bidding. A second test is based on understanding the source of frictions the shock alleviates. By means of triple difference-in-differences interaction terms and data on final property owners, the improved matching at the auction is driven by accessibility of the courthouse and by the entrance of local buyers who buy and hold properties. All in all, this evidence corroborates that the shock removes demand frictions, enables retail players to participate in a market, and it is clean from any supply effects over such a short estimation window.

I also analyze the REO market and ex-ante credit decisions. Following the online bidding shock, properties that are not sold through the auction do not become worse. Furthermore, considering the properties sold at the auction and those through the private market, foreclosure assets spend a smaller amount of time on the market. As per ex-ante credit supply decisions, lenders are found to start extending more loans – and at lower interest rates – as a response to smaller loss given default in the future. This better liquidation payoff, however, is not translated into higher foreclosure probability conditional on borrower default. This may be due to the imperfect data sample used in the analysis though, and requires further research which would be important for a full welfare assessment.

The evidence presented in this paper is consistent with the idea that onsite auctions – part of the foreclosure process – are costly to access and therefore incur efficiency losses. Removing bidding frictions by means of technology can improve buyer-seller matching in this important segment of the real estate market. Faster reallocation of risky distressed assets from the bank sector to the household sector generate substantial welfare gains. Moreover, the results are line with recommendations advocating a necessary government efforts to streamlining the foreclosure process (Fisher et al., 2015; Gerardi et al., 2015).

Tables

Table 1: Summary statistics

	Panel A: Full sample					
	Source	Mean	Std.Dev.	P5	P95	Observ.
$\text{AuctSucc}_{i,c,t}$	RPR	.1809	.3849	0	1	606,802
$\text{AuctDisc}_{i,c,t}$	RPR	.0797	.2051	-.2616	.4269	60,571
$\text{Treated}_{i,c,t}$	realauc	.5184	.4997	0	1	606,802
$\text{Post}_{i,c,t}$	realauc	.5436	.4981	0	1	606,802
$\text{HouseAge}_i, c, t$	RPR	26.806	19.734	4	61	441,264
$\ln(\text{Size})_{i,c,t}$	RPR	7.507	.4111	6.880	8.202	430,162
$\text{NoResUnts}_{i,c,t}$	RPR	1.022	6.000	1	1	423,589
$\text{StrucQual}_{i,c,t}$	RPR	3.101	.8255	2	4	413,735
$\ln(\text{Fcl})_{c,t\in(-12;0)}$	FLCourts	6.376	1.364	3.543	8.246	582,057
$\ln(\text{NonFcl})_{c,t\in(-12;0)}$	FLCourts	5.555	1.207	3.554	7.385	582,057
AOoS	RPR	.1071	.3093	0	1	34,774
AProfss	RPR	.1664	.3724	0	1	108,703
AFlip	RPR	.1731	.3783	0	1	109,747
AMultiProp	RPR	.3256	.4686	0	1	108,703
$\text{NoAuct}_{c,t}$	RPR	.4853	.3500	.071	1.175	606,802
$\text{Remoteness}_{c,t}$	FLCourts	.9358	.0897	.8437	.9925	606,802
$\text{b-iDist}_{i,c,t}$	RPR	.4046	.6126	0	2.080	65,015
$\text{c-iDist}_{i,c,t}$	RPR	.0288	.0528	0	.1310	321,237
$\text{c-bDist}_{i,c,t}$	RPR	.4197	.6016	.0046	2.026	76,189
$\text{REODisc}_{i,c,t}$	RPR	.0373	.2274	-.3480	.4164	123,526
$\text{ROoS}_{i,c,t}$	RPR	.3626	.4808	0	1	81,434
$\text{RProfss}_{i,c,t}$	RPR	.3388	.4530	0	1	193,375
$\text{REOt2s}_{i,c,t}$	RPR	4.748	7.622	0	20	303,721
$\text{REOt2s}_{i,c,t}$ (exclSucc)	RPR	7.434	8.426	1	28	193,974
$\text{Accept}_{i,c,t}$	HMDA	.7228	.4476	0	1	2,726,834
$\text{Modify}_{i,c,t}$	SFLL	.0027	.0517	0	0	14,192

	Panel B: Changes in foreclosure outcomes and property characteristics					
	Pre-event			Post-event		
	Treated	Control	T-C	Treated	Control	T-C
$\text{AuctSucc}_{i,c,t}$	.1447	.1916	-.0469***	.1957	.1905	.0052***
$\text{AuctDisc}_{i,c,t}$	.1415	.0753	.0661***	.0673	.0586	.0086***
$\text{HouseAge}_i, c, t$	28.771	23.581	5.190***	30.420	25.339	5.081***
$\ln(\text{Size})_{i,c,t}$	7.471	7.464	.007***	7.481	7.458	.022***
$\text{NoResUnts}_{i,c,t}$	1.010	1.008	.001**	1.010	1.008	.002***
$\text{StrucQual}_{i,c,t}$	3.126	3.069	.057***	3.124	3.120	.004

Note: This table shows the data source (Real Property Roll, *realauction.com*, *FLCourts.org*, the Home Mortgage Disclosure Act (HMDA), and Freddie Mac Single-Family Loan-Level (SFLL) data-set) and summary statistics (mean, standard deviation, main percentiles) of the variables used. Panel B compares sample means of the main variable for the Treated and Control groups, before and after the shock.

Table 2: Electronic Bidding and Foreclosure Auction Success

Dep. var.: AucSucc$_{i,c,t}$	(1)	(2)	(3)	(4)	(5)
Treated$_c$ × $Post_t$	.0542***	.0529***	.0456**	.0503***	.0493***
	(3.04)	(3.00)	(2.23)	(2.75)	(2.78)
Treated$_c$	-.0469**	-.0530***			
	(-2.57)	(-3.25)			
HouseAge$_{i,c,t}$		-.00127***	-.00105***	-.000811***	-.000867***
		(-5.34)	(-4.67)	(-5.45)	(-6.17)
ln(Size)$_{i,c,t}$		-.0280***	-.0385***	-.0282***	-.0247***
		(-3.76)	(-7.79)	(-7.97)	(-8.02)
NoResUnts$_{i,c,t}$		-.00007***	.00097	.00005	-.00046
		(-9.12)	(.72)	(.06)	(-.54)
StrucQual$_{i,c,t}$		-.0115**	-.00693**	-.00058	-.00089
		(-2.13)	(-2.12)	(-.31)	(-.49)
Border × Month FE	✓	✓	✓	✓	✓
Geog FE	X	X	c	z	n
# of Observations	441,264	411,519	411,519	331,316	350,056
R^2	.046	.049	.063	.081	.092
adj. R^2	.044	.047	.061	.075	.076

Note: This table presents OLS coefficient estimates of regression equation 1. The dependent variable $AucSucc_{i,c,t}$ takes value 1 if foreclosed property i in county c is sold to third-party bidders at the auction in month t, and zero otherwise. The dummy variable $Treated_c$ takes value 1 if county c adopts the electronic bidding policy at some point before 2020, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. Control property variables are $HouseAge_{i,c,t}$, $ln(Size_{i,c,t})$, $NoResUnts_{i,c,t}$ and $StrucQual_{i,c,t}$. Fixed effects include county border group times month and either county c, zip code z, or census tract n fixed effects. Standard errors clustered at border-by-county level. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 3: Electronic Bidding and Foreclosure Auction Discount

Dep. var.: $\text{AucDisc}_{i,c,t}$	(1)	(2)	(3)	(4)	(5)
$\text{Treated}_c \times Post_t$	-.0485***	-.0435***	-.0263**	-.0279*	-.0337**
	(-4.96)	(-5.06)	(-2.08)	(-1.77)	(-2.18)
Treated_c	.0518***	.0385***			
	(3.02)	(2.68)			
$\text{HouseAge}_{i,c,t}$		.00205***	.00193***	.00192***	.00198***
		(12.66)	(13.98)	(10.40)	(11.46)
$\ln(\text{Size})_{i,c,t}$		-.0453***	-.0295***	-.0205***	-.00903*
		(-5.76)	(-5.90)	(-4.38)	(-1.91)
$\text{NoResUnts}_{i,c,t}$		.0609***	.0495***	.0399***	.0443***
		(4.56)	(4.45)	(3.86)	(3.89)
$\text{StructQual}_{i,c,t}$		.0188	-.00128	.00244	.00394
		(1.62)	(-.70)	(.78)	(1.64)
Border × Month FE	✓	✓	✓	✓	✓
Geog FE	X	X	c	z	n
# of Observations	60,562	58,929	58,928	50,346	51,449
R^2	.090	.132	.168	.221	.288
adj. R^2	.080	.122	.157	.193	.225

Note: This table shows the results of OLS regressions on equation 1. The dependent variable $AucDisc_{i,c,t}$ is 1 minus the ratio of the auction final price to the market value of property i. The dummy variable $Treated_c$ takes value 1 if county c adopts the electronic bidding policy at some point before 2020, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. Control property variables are $HouseAge_{i,c,t}$, $ln(Size_{i,c,t})$, $NoResUnts_{i,c,t}$ and $StrucQual_{i,c,t}$. Fixed effects include county border group-times-month and either county c, zip code z, or census tract n fixed effects. Standard errors clustered at border-by-county level. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 4: Instrumental Variable

Dep. var.:	$\text{AucSucc}_{i,c,t}$		$\text{AucDisc}_{i,c,t}$	
	(1)	(2)	(3)	(4)
$\text{Treated}_c \times Post_t$	.0932***	.0916***	-.0559***	-.0575***
	(2.86)	(3.10)	(-2.70)	(-3.00)
$\text{HouseAge}_{i,c,t}$	-.00083***	-.00083***	.00190***	.00190***
	(-6.00)	(-6.00)	(11.56)	(11.56)
$\ln(\text{Size})_{i,c,t}$	-.0241***	-.0241***	-.00989*	-.0099*
	(-7.61)	(-7.62)	(-1.98)	(-1.98)
$\text{NoResUnts}_{i,c,t}$	-.0010	-.0010	.0462***	.0462***
	(-.49)	(-.49)	(4.01)	(4.01)
$\text{StrucQual}_{i,c,t}$	-.00169	-.00169	.00483**	.00483**
	(-.99)	(-.99)	(2.16)	(2.16)
Border × Month FE	✓	✓	✓	✓
Geog FE	n	n	n	n
# of Observations	335,928	335,928	48,211	48,211
R^2	.001	.001	.018	.018
adj. R^2	-.001	-.001	.004	.004
1st Stage Dep. var.:	$\text{Treated}_c \times Post_t$			
IV:	$Fcl_{c,t\in(-12;0)}$	$NonFcl_{c,t\in(-12;0)}$	$Fcl_{c,t\in(-12;0)}$	$NonFcl_{c,t\in(-12;0)}$
	(1)	(2)	(3)	(4)
$\ln(\text{Filings})_{c,t\in(0;-12)}$ $\times Post_t$	.387***	.399***	.519***	.498***
	(4.37)	(5.61)	(4.57)	(5.81)
Kleibergen-Paap rk Wald F stat	19.07	31.49	20.84	33.70

Note: This table shows the results of 2SLS regressions on equation 1. In the top panel (second stage), the dependent variable in the first two columns is $AucSucc_{i,c,t}$ which takes value 1 if foreclosed property i in county c is successfully sold at the auction in month t to third-party buyers, and zero otherwise. In columns 3 and 4, the dependent variable is $AucDisc_{i,c,t}$ which is defined as 1 minus the ratio of the auction final price to the market value of the property. In the bottom panel, the first stage estimation instruments the interaction term $Treated_t \times Post_t$ with incoming court filings averaged across the 12 months before the adoption date: foreclosure cases (columns 1 and 2) and non-foreclosure civil (columns 3 and 4) cases. $Treated_c$ takes value 1 if county c adopts the electronic bidding policy at some point before 2020, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. Property-level controls are $HouseAge_{i,c,t}$, $ln(Size_{i,c,t})$, $NoResUnts_{i,c,t}$ and $StrucQual_{i,c,t}$. Census tract fixed effects and border times month fixed effects are included in all specifications. Standard errors clustered at border-by-county level. *t-statistics* are in parentheses.*, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 5: Robustness exercises

Dep. var.: $\text{AuctSucc}_{i,c,t}$	Placebo (1)	Awareness (2)	Donut (3)	LateTreat (4)	NotYetTr (5)	wReg (6)	Supply (7)
$\text{Treated}_c \times Post_t$	.0042		.0526***	.0513***	.0598***	.0452***	.0466**
	(.16)		(2.99)	(2.79)	(3.18)	(2.97)	(2.43)
Post_t		.0081					
		(.81)					
$\text{HouseAge}_{i,c,t}$	-.00081***	-.0009*	-.00088***	-.0010***	-.0010***	-.00069***	-.00089***
	(-4.34)	(-1.76)	(-5.90)	(-5.87)	(-7.14)	(-3.72)	(-6.34)
$\ln(\text{Size})_{i,c,t}$	-.0211***	-.0191	-.0242***	-.0248***	-.0232***	-.0301***	-.0258***
	(-4.54)	(-1.45)	(-7.66)	(-6.43)	(-6.89)	(-6.23)	(-8.11)
$\text{NoResUnts}_{i,c,t}$	.00112	.0945***	-.00058	-.0023	-.00076	.00298	-.00053
	(.87)	(3.93)	(-.70)	(-.30)	(-.98)	(.27)	(-.61)
$\text{StrucQual}_{i,c,t}$	.00435	-.0192**	.00089	-.00177	-.00151	-.00151	.00126
	(1.18)	(-2.37)	(.47)	(-.74)	(-.80)	(-.58)	(-.69)
$\text{Tr}_c \times Post_t \times GovAg_{i,c,t}$							.0763
							(1.43)
Border×Mnth FE	✓	x	✓	✓	✓	✓	✓
Geog FE	n	cb,n	n	n	n	n	n
# of Observations	171,702	12,355	328,229	249,810	305,721	249,902	350,065
R^2	.088	.087	.095	.093	.094	.087	.095
adj. R^2	.072	.028	.078	.081	.078	.075	.079

Note: This table presents OLS estimated coefficients of regression equation 1, starting from the specification in the last column of table 2. Column 1 excludes actual treated counties and changes the dummy variable $Treated_c$ taking value 1 for the closest (in terms of population) control county c, and zero otherwise. Column 2 focuses only on zip codes that are less than five miles away from a county border in control counties, while column 3 excludes $\leq 5m$ zip codes in both treated and control counties. In column 4, the sample is restricted to county borders with pre-shock window longer than 16 months. Column 5 drops "not-yet-treated" counties from the control group. Column 6 estimates the baseline regression by means of Weighted least squares (WLS), with weights equal to the inverse of the number of control units in a border group. Column 7 adds the dummy $GovtAg_{i,c,t}$ taking value 1 if the foreclosing lender is a Government agency (including HUD, Fannie Mae, and Freddie Mac), and zero otherwise, to the baseline model. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. Property-level controls are $HouseAge_{i,c,t}$, $ln(Size_{i,c,t})$, $NoResUnts_{i,c,t}$ and $StrucQual_{i,c,t}$. Census tract fixed effects and border-times-month fixed effects are included in all specifications. Standard errors clustered at border-by-county level. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 6: Electronic Bidding and Foreclosure Auction Buyers

Dep. var.:	$\text{OutState}_{i,c,t}$ (1)	$\text{b-iDist}_{i,c,t}$ (2)	$\text{b-cDist}_{i,c,t}$ (3)	$\text{Profssnal}_{i,c,t}$ (4)	$\text{MultiProp}_{i,c,t}$ (5)	$\text{Flip}_{i,c,t}$ (6)
$\text{Treated}_c \times Post_t$	-.0547**	-.0613*	-.0696**	-.0495***	-.0327**	-.0251**
	(-2.00)	(-1.81)	(-1.86)	(-4.22)	(-1.72)	(-2.47)
$\text{HouseAge}_{i,c,t}$	-.00107***	-.00067***	-.00078***	.000093	-.00009	.00011
	(-5.24)	(-3.36)	(-3.67)	(.47)	(.40)	(.63)
$\ln(\text{Size})_{i,c,t}$	.00211	.0300***	.0293***	-.0338***	-.0771***	-.0102
	(.35)	(3.08)	(2.81)	(-4.65)	(-12.39)	(-1.55)
$\text{NoResUnts}_{i,c,t}$	.0551**	-.0110	-.0098	-.00321	.0338*	-.0176
	(2.54)	(-.57)	(-.46)	(-.18)	(1.71)	(-.77)
$\text{StrucQual}_{i,c,t}$	.0114*	-.00642	-.00659	-.00530*	-.00704**	.0061**
	(1.95)	(-1.26)	(-1.21)	(-1.87)	(-2.21)	(2.33)
Border×Mnth FE	✓	✓	✓	✓	✓	✓
Geog FE	n	n	n	n	n	n
# of Observations	25,167	64,022	59,815	62,615	62,615	62,615
R^2	.211	.187	.191	.238	.258	.147
adj. R^2	.082	.121	.125	.178	.199	.080

Note: This table presents OLS estimated coefficients of regression equation 1. In column 1, the dependent variable $OutState_{i,c,t}$ takes value 1 if the buyer of foreclosed property i had not the main residence in Florida, and zero otherwise. The dependent variable in column 2 is the distance between the zip code of the buyer b's previous residence and that of the acquired property i in thousand miles. In column 3, the distance is calculated between buyer b and courthouse c hosting the auction. $Profssnal_{i,c,t}$ is a dummy taking value 1 if the buyer of the auctioned property is a financial institution or real estate company, and zero otherwise. In column 5, $MultiProp_{i,c,t}$ takes value 1 if the buyer of the auctioned property owned more that one house in Florida in the previous year, and zero otherwise. $Flip_{i,c,t}$ is equal to 1 if the auction buyer flips the acquired property within the next 4 years, and zero otherwise. The dummy variable $Treated_c$ takes value 1 if county c adopts the electronic bidding policy at some point before 2020, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise.Property-level controls are $HouseAge_{i,c,t}$, $ln(Size_{i,c,t})$, $NoResUnts_{i,c,t}$ and $StrucQual_{i,c,t}$. Census tract fixed effects and border-times-month fixed effects are included in all specifications. Standard errors clustered at border-by-county level. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 7: Triple Difference-in-Differences

Dep. var.:	AuctSucc$_{i,c,t}$			
DDD Channel:	Remote$_c$ (1)	c-iDist$_i$ (2)	NoAuct$_{c,t}$ (3)	Quality$_i$ (4)
Treated$_c$ × $Post_t \times Ch$	.461**	.517*	.118**	.0260**
	(2.24)	(1.80)	(2.48)	(2.40)
Treated$_c$ × $Post_t$	-.381**	.0426*	-.0257	.0422**
	(-2.08)	(1.77)	(-1.57)	(2.38)
HouseAge$_{i,c,t}$	-.000867***	-.000955***	-.000868***	-.000866***
	(-6.16)	(-6.03)	(-6.18)	(-6.26)
ln(Size)$_{i,c,t}$	-.0249***	-.0250***	-.0247***	-.0242***
	(-8.07)	(-7.62)	(-7.99)	(-7.92)
NoResUnts$_{i,c,t}$	-.000423	-.00086	-.00036	-.00044
	(-.50)	(-1.01)	(-.42)	(-.51)
StrucQual$_{i,c,t}$	-.00082	-.00143	-.00073	.00480
	(-.47)	(.70)	(-.42)	(1.65)
CrossInteractions	✓	✓	✓	✓
Border×Mnth FE	✓	✓	✓	✓
Geog FE	n	n	n	n
# of Observations	350,056	306,907	350,056	350,065
R^2	.093	.093	.093	.092
adj. R^2	.077	.076	.077	.076

Note: This table presents OLS estimated coefficients of regression equation 1. The dependent variable $AucSucc_{i,c,t}$ takes value 1 if foreclosed property i in county c is successfully sold at the auction in month t to third-party buyers, and zero otherwise. The dummy variable $Treated_c$ takes value 1 if county c adopts the electronic bidding policy at some point before 2020, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. Each specification has a different variable interacted with $Treated_c \times Post_t$. The first column adds a court remoteness index, defined as 1 minus the fraction of the population in the court zip code to the total population in the county, and zero otherwise. The distance between the courthouse and property i is instead included in column 2. The channel in column 3 is the number of foreclosure auctions county c experiences in month t. Column 4 explores any heterogeneous effects along the quality of the house including the triple interaction term a dummy equal to one if the quality of the property structure is above average (as assessed by property appraisers), and zero otherwise. Control variables are $HouseAge_{i,c,t}$, $ln(Size_{i,c,t})$, $NoResUnts_{i,c,t}$ and $StrucQual_{i,c,t}$. Census tract fixed effects and border-times-month fixed effects are included in all specifications. Standard errors clustered at border-by-county level. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 8: REO Market

Dep. var.:	$\text{REODisc}_{i,c,t}$ (1)	$\text{REODisc}_{i,c,t}$ (2)	$\text{OoS}_{i,c,t}$ (3)	$\text{Profssnal}_{i,c,t}$ (4)	$\text{T2Sell}_{i,c,t}$ (5)	$\text{T2Sell}_{i,c,t}$ (6)
$\text{Treated}_c \times Post_t$	.0148**	.0127	-.0124	.0230**	.0660***	.0450***
	(2.10)	(1.66)	(-.62)	(1.96)	(4.95)	(2.52)
$\text{HouseAge}_{i,c,t}$	.00309***	.00345***	-.000519***	.000091	-.00296***	.00270***
	(19.66)	(16.64)	(-2.82)	(.56)	(-17.54)	(12.33)
$\ln(\text{Size})_{i,c,t}$	-.0206**	-.0233**	.0312***	-.0117*	-.228***	.134***
	(-2.34)	(-2.42)	(4.07)	(-1.89)	(-27.52)	(13.16)
$\text{NoResUnts}_{i,c,t}$	.0236**	.0263*	-.0308*	.0149	-.0424	-.0142
	(2.18)	(1.83)	(-1.77)	(.92)	(-1.25)	(-.43)
$\text{StrucQual}_{i,c,t}$	.0109***	.0128***	-.00863*	-0.0073*	.00798**	.01934***
	(3.39)	(3.41)	(-1.73)	(-1.86)	(2.03)	(3.25)
Border×Mnth FE	✓	✓	✓	✓	✓	✓
Geog FE	n	n	n	n	X	z
# of Observations	104,938	96,894	55,237	119,073	133,667	113,954
R^2	.340	.345	.177	.151	X	X
adj. R^2	.305	.308	.096	.110	X	X

Note: This table presents OLS estimated coefficients of regression equation 1 yet focusing on the sample of REOs (unsuccessful auctions). In column 1 and 2, the dependent variable $REODisc_{i,c,t}$ is defined as 1 minus the ratio of the REO asset final price to its market value assessed by property appraisers at the end of the previous year. The dependent variable $OoS_{i,c,t}$ in column 3 takes value 1 if the buyer of REO asset i did not reside in Florida, and zero otherwise. $Profssnal_{i,c,t}$ is a dummy taking value 1 if the buyer of the auctioned property is a financial institution or real estate company, and zero otherwise. Column 5 and 6 include the dependent variable $T2Sell_{i,c,t}$ which is the time (in months) elapsed between the auction date and the REO sale. The dummy variable $Treated_c$ takes value 1 if county c adopts the electronic bidding policy at some point before 2020, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. Census tract fixed effects and border times month fixed effects are included in all specifications. Standard errors clustered at county-by-border level. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 9: Ex-ante Credit

Dep. var.:	$\text{Accept}_{i,c,t}$			$\text{HPrice}_{i,c,t}$		$\text{Modify}_{i,c,t}$	
Model:	OLS		IV	OLS		Duration	
	(1)	(2)	(3)	(4)		(5)	(6)
$\text{Tr}_c \times P_t$	.00565***	-.0317***	.0221***	-.0224*	$\text{Tr}_c \times Pt_t$	-.406	.914
	(3.79)	(-9.68)	(4.73)	(-1.90)		(-1.08)	(-.12)
$\text{Tr}_c \times P_t \times Risky_{i,c,t}$		.100***					
		(8.24)					
$\text{LoanAmt}_{i,c,t}$	-.0282**	-.0123	-.0262***	-.0764***	$\text{LAge}_{i,c,t}$	-.0039	.996
	(-2.26)	(-1.47)	(-4.13)	(-3.60)		(-.46)	(-.70)
$\text{Minority}_{i,c,t}$	-.0798***	-.0775***	-.0760***	.0705***	$\text{LTV}_{i,c,t}$	.0094	1.012
	(-10.31)	(-10.23)	(-17.18)	(3.03)		(.47)	(.75)
$\text{DTI}_{i,c,t}$	-.00152***	-.0119***	-.00144***	-.00120	$\text{DTI}_{i,c,t}$	.002***	1.002***
	(-2.85)	(-2.86)	(-3.49)	(-1.56)		(2.67)	(2.82)
$\text{Female}_{i,c,t}$	-.0170***	-.0127***	-.0170***	.00578	$\text{FICO}_{i,c,t}$	-.0025	.998
	(-5.99)	(-4.88)	(-15.08)	(1.28)		(-.02)	(-.60)
$\text{Jumbo}_{i,c,t}$	-.0899***	-.0893***	-.0915***	.108***			
	(-7.14)	(-7.43)	(-13.67)	(-3.50)			
$\text{Coapplicant}_{i,c,t}$	.0467***	.0386***	.0474***	-.0171***			
	(13.06)	(10.62)	(25.26)	(-3.50)			
Border×Mnth FE	✓	✓	✓	✓		✓	✓
Geog FE	n	n	n	n		z	z
# of Obs.	2,442,085	2,442,085	2,226,925	1,780,399		13,880	13,880
R^2	.060	.066	.009	.082			
adj. R^2	.058	.063	.009	.078			

Note: This table presents estimated coefficients of regression equation 2. The dependent variable in columns 1-3 is $Accept_{i,c,t}$, a dummy variable equal to one if mortgage application i to finance a house purchase in county c in year t is accepted, and zero if rejected. The policy dummy $Treated_c$ is equal to one if county c adopts the electronic bidding technology at some point in time, and zero otherwise. $Post_t$ is a time dummy taking value 1 after policy adoption, and zero otherwise. The dummy $Risky_{i,c,t}$ takes value one if the Debt-To-Income ratio of the borrower is larger than the county c median in year t, and zero otherwise. Coefficients in column 3 are estimated with 2SLS, instrumenting the interaction variable $Treated_c \times Post_t$ with the interaction between $Post_t$ and the logarithm of the number of non-foreclosure non-foreclosure($NonForecl_{c,t\in(-12,0)}$) filings county c receives over the 12 months before treatment. The dependent variable in column 4 is the dummy $HPrice_{i,c,t}$, which takes value one if the interest rate charged on accepted loans is higher than a comparable Treasury rate. Control variables include the amount of the loan application, a minority indicator indicating the applicant's ethnicity group, Debt-to-Income ratio, a gender indicator, a securitization conforming *jumbo*) indicator, and presence of co-borrowers. Census tract fixed effects and border-times-month fixed effects are included in all specifications. Standard errors clustered at bank and county level. Columns 5 and 6 estimate hazard models with a $Modify_{i,c,t}$ dummy variable taking value of one if a borrower receives modification conditional on default, and zero if she restores her mortgage or receives foreclosure. *t-statistics* are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Figures

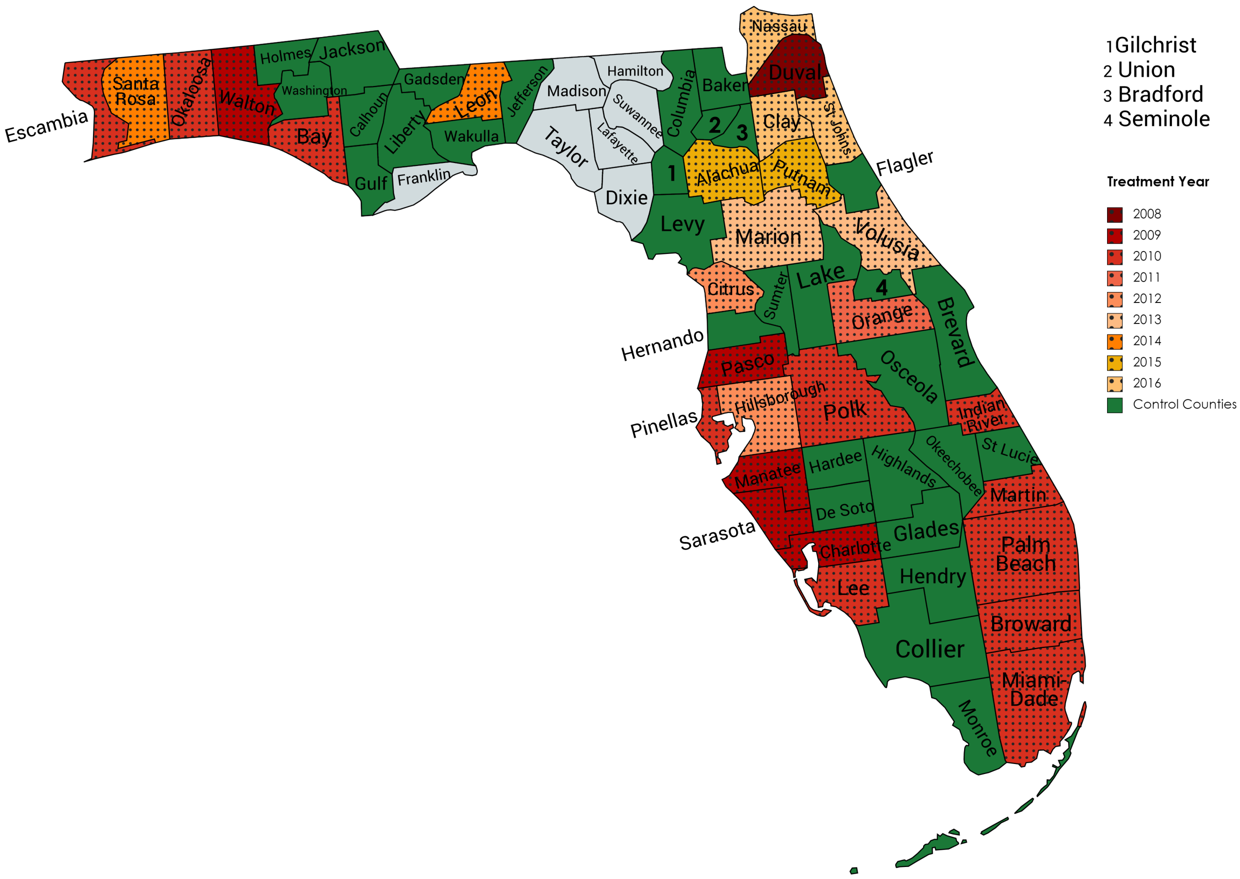

Figure 1: Treatment incidence and timing. This figure shows the year in which Florida counties adopted (dotted) the online bidding technology, those that never adopt but adjoin adopters (green) and those that never adopt and do not adjoin adopters (light blue). Adoption decisions are considered up to, and including, 2019.

Figure 2: Auction success rates, defined as the ratio between the number of third-party foreclosure auction sales and the total number of auctions in a given month. Shaded areas represent the 95% confidence level error bounds. The values are averaged within treated (blue) counties and control (red) counties per month.

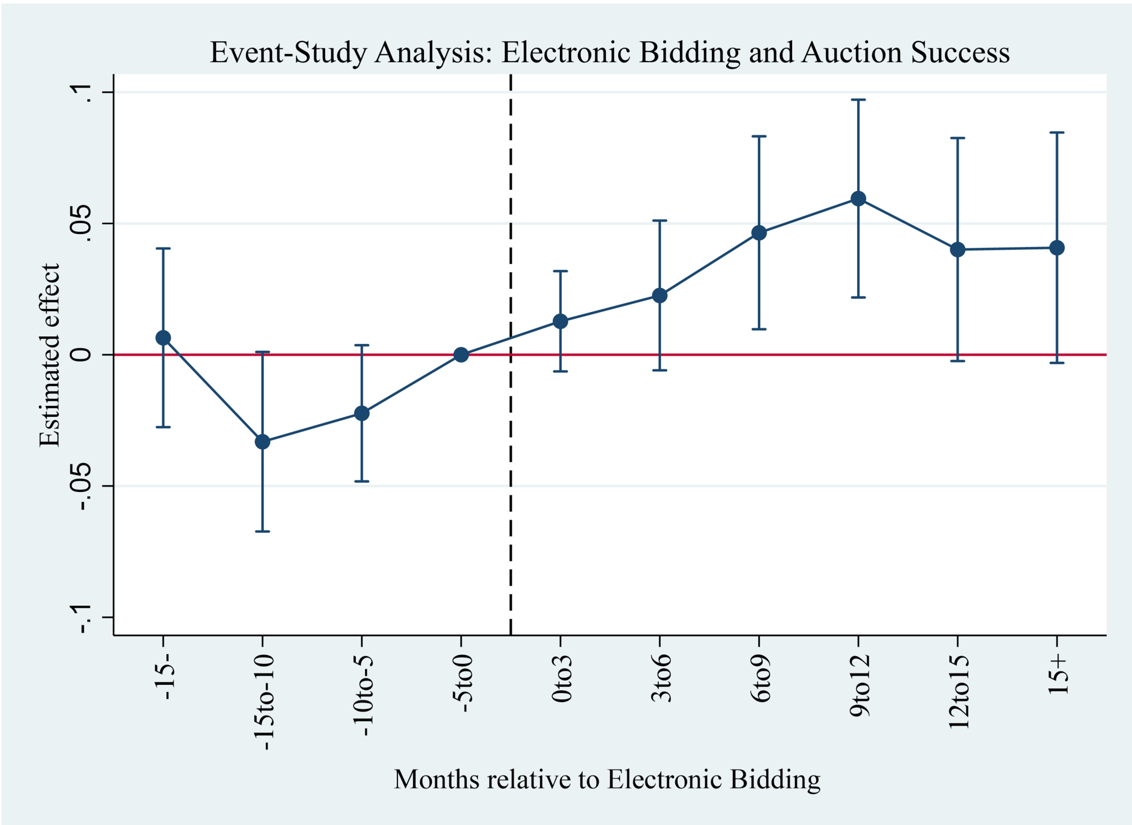

Figure 3: Event study estimates of electronic bidding on foreclosure auction success according to equation (1). The point estimates are based on interactions between treatment and time indicators grouped by 3 months replacing the dummy $Post_t$ in model 1.

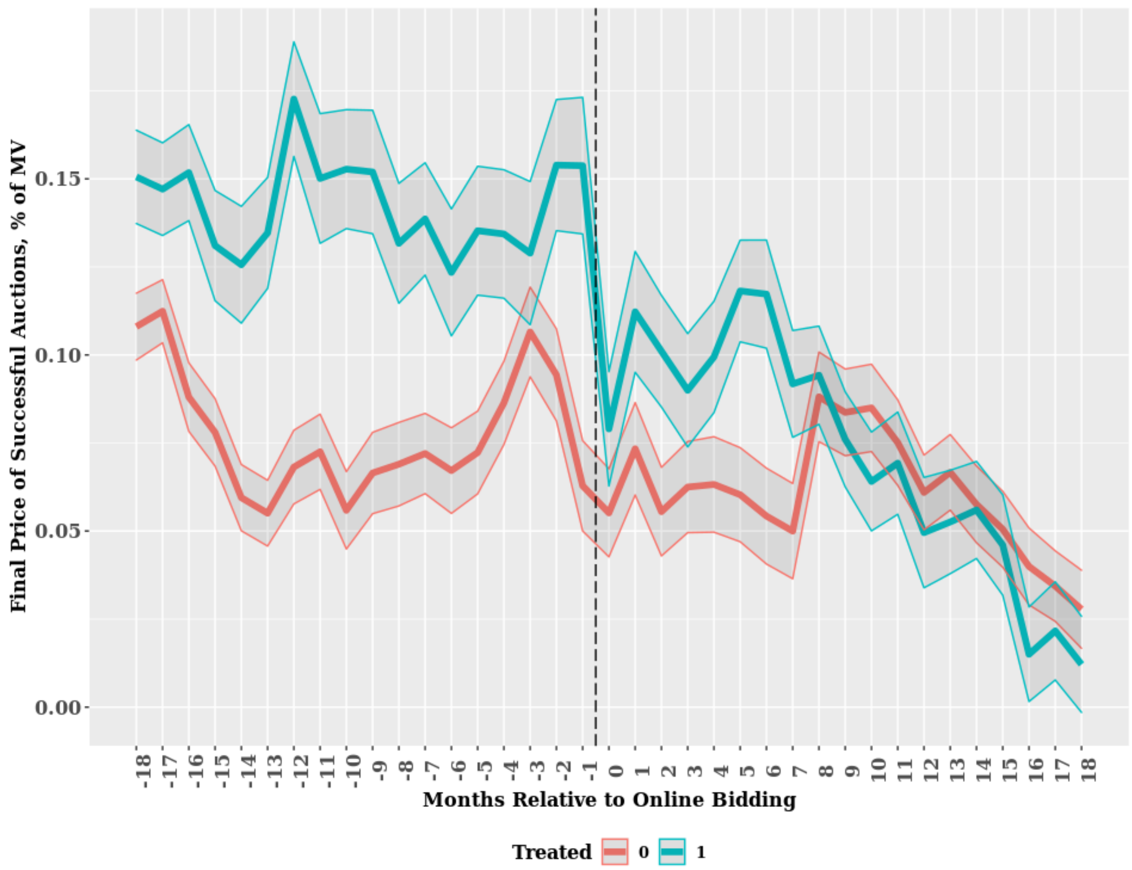

Figure 4: Auction discount, defined as 1 minus the ratio between the final price of a third-party foreclosure auction sale and the market value of the property assessed by county appraisers the year before. Shaded areas represent the 95% confidence level error bounds. The values are averaged within treated (blue) counties and control (red) counties per month.

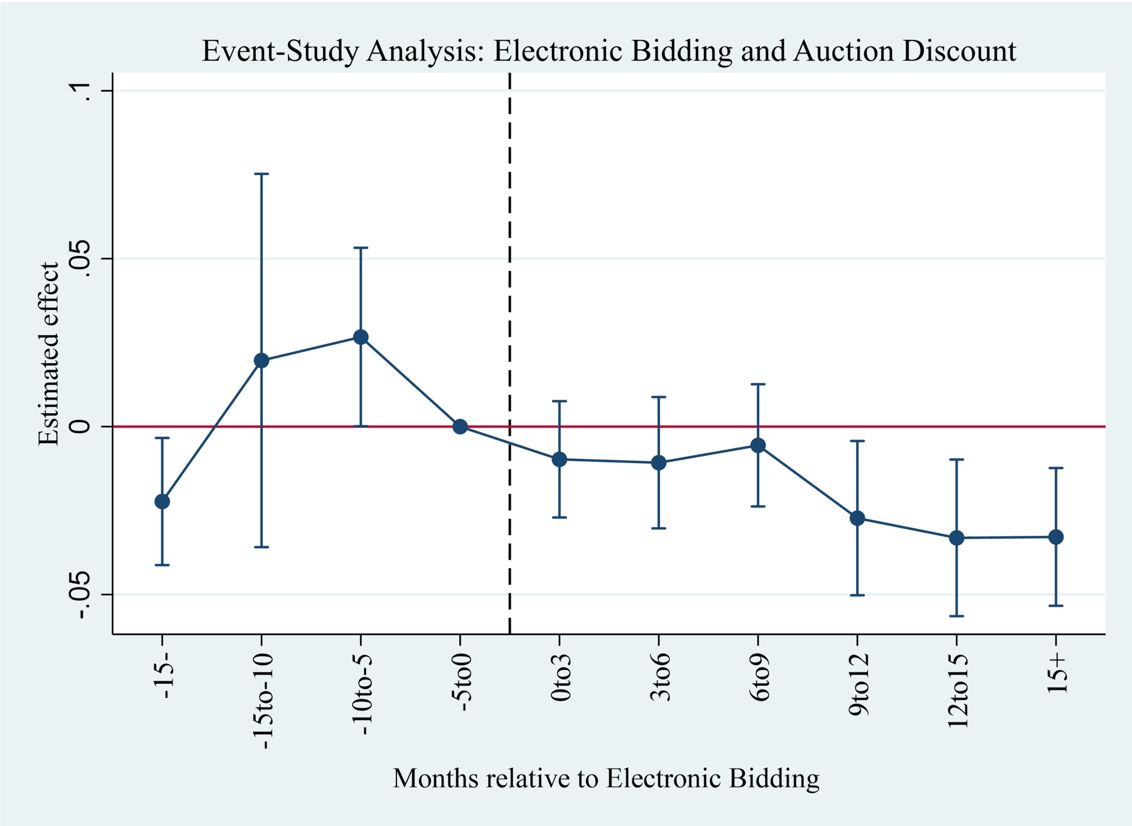

Figure 5: Event study estimates of electronic bidding on foreclosure auction discount. The point estimates are based on time indicators replacing the dummy $Post_t$ in model 1.

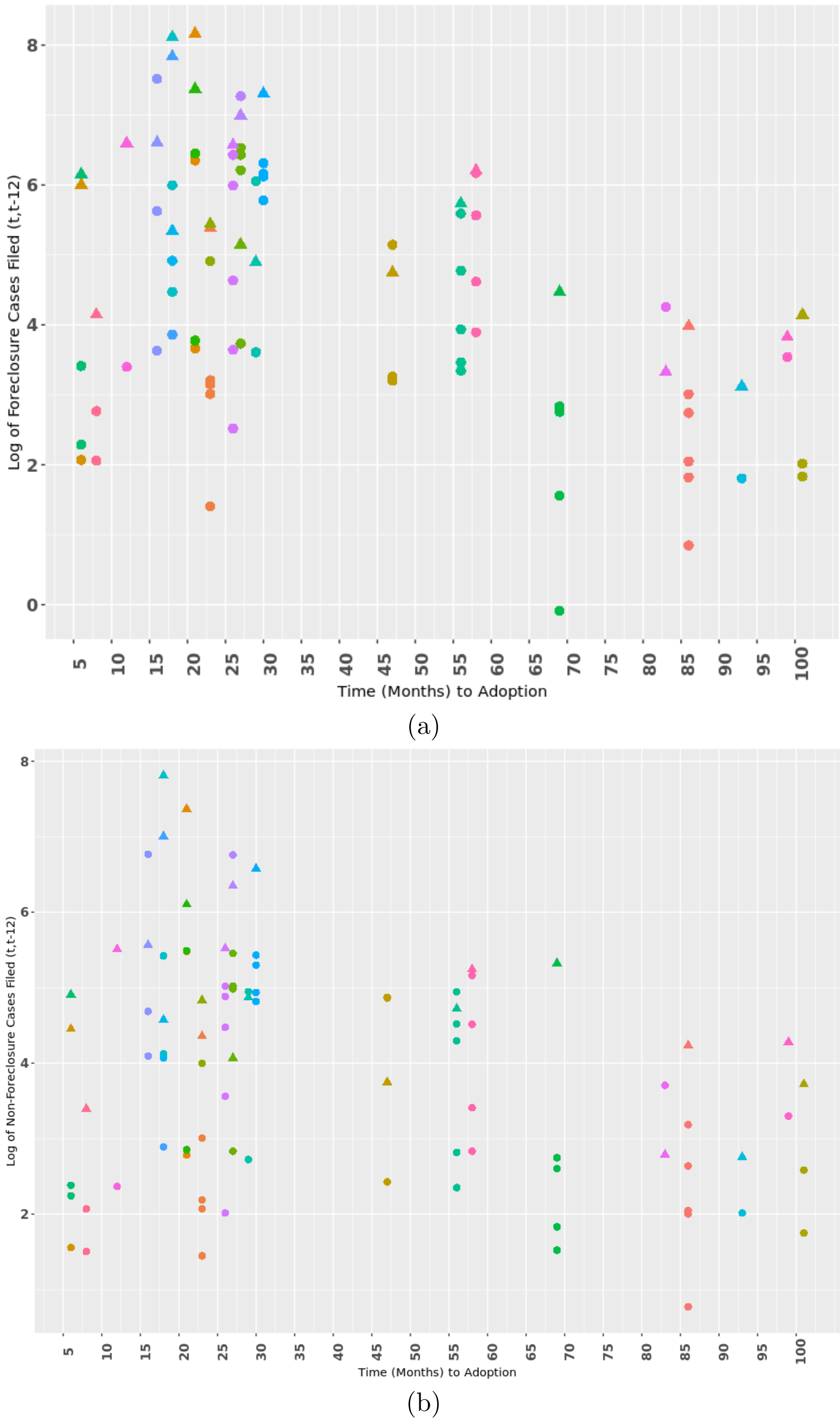

Figure 6: County exposure to legal filings by county border group (color) across adoption times (x-axis). Triangles denote adopters, and circles non-adopting counties adjoining the adopter. Panel A plots the legal filings related to foreclosure cases, while panel B to non-foreclosure (civil) cases.

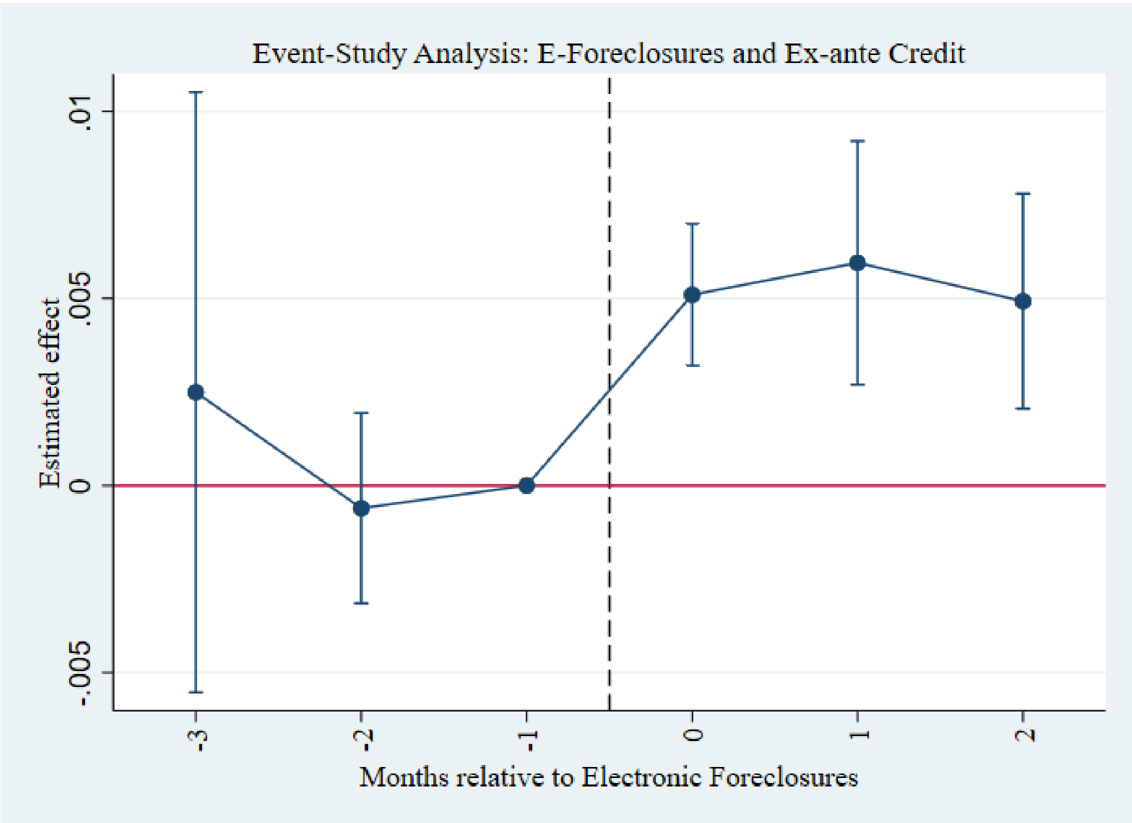

Figure 7: Event study estimates of the impact of electronic bidding on ex-ante mortgage application acceptance. The point estimates are based on time indicators replacing the dummy $Post_t$ in model 2.

References

Allen, F. and Santomero, A. M. (1997). The theory of financial intermediation. *Journal of banking & finance*, 21(11-12):1461–1485.

Anenberg, E. and Kung, E. (2014). Estimates of the size and source of price declines due to nearby foreclosures. *American Economic Review*, 104(8):2527–51.

Asquith, P., Gertner, R., and Scharfstein, D. (1994). Anatomy of financial distress: An examination of junk-bond issuers. *The quarterly journal of economics*, 109(3):625–658.

Baker, A., Larcker, D. F., and Wang, C. C. (2021). How much should we trust staggered difference-in-differences estimates? *Available at SSRN 3794018*.

Bakos, J. Y. (1997). Reducing buyer search costs: Implications for electronic marketplaces. *Management science*, 43(12):1676–1692.

Bakos, Y. (1998). The emerging role of electronic marketplaces on the internet. *Communications of the ACM*, 41(8):35–42.

Benmelech, E., Garmaise, M. J., and Moskowitz, T. J. (2005). Do liquidation values affect financial contracts? evidence from commercial loan contracts and zoning regulation. *The Quarterly Journal of Economics*, 120(3):1121–1154.

Besley, T. and Case, A. (2000). Unnatural experiments? estimating the incidence of endogenous policies. *The Economic Journal*, 110(467):672–694.

Bogan, V. (2008). Stock market participation and the internet. *Journal of Financial and Quantitative Analysis*, 43(1):191–211.

Bollaert, H., Lopez-de Silanes, F., and Schwienbacher, A. (2021). Fintech and access to finance. *Journal of corporate finance*, 68:101941.

Bongaerts, D., Mazzola, F., and Wagner, W. (2021). Fire sale risk and credit. *Available at SSRN 3783199*.

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6):2201–2238.

Burkhart, A. M. (2017). Fixing foreclosure. *Yale L. & Pol'y Rev.*, 36:315.

Campbell, J. Y., Giglio, S., and Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, 101(5):2108–31.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Chinloy, P., Hardin, W., and Wu, Z. (2017). Foreclosure, reo, and market sales in residential real estate. *The Journal of Real Estate Finance and Economics*, 54(2):188–215.

Clauretie, T. M. and Daneshvary, N. (2009). Estimating the house foreclosure discount corrected for spatial price interdependence and endogeneity of marketing time. *Real Estate Economics*, 37(1):43–67.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.

Currie, J. and Tekin, E. (2015). Is there a link between foreclosure and health? *American Economic Journal: Economic Policy*, 7(1):63–94.

Dagher, J. and Sun, Y. (2016). Borrower protection and the supply of credit: Evidence from foreclosure laws. *Journal of Financial Economics*, 121(1):195–209.

Daneshvary, N., Clauretie, T., and Kader, A. (2011). Short-term own-price and spillover effects of distressed residential properties: The case of a housing crash. *Journal of Real Estate Research*, 33(2):179–208.

Diamond, P. A. (1982). Aggregate demand management in search equilibrium. *Journal of political Economy*, 90(5):881–894.

Donner, H. (2020). Determinants of a foreclosure discount. *Journal of Housing and the Built Environment*, 35(4):1079–1097.

Duflo, E. (2001). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American economic review*, 91(4):795–813.

Ellul, A., Jotikasthira, C., and Lundblad, C. T. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, 101(3):596–620.

Favara, G. and Giannetti, M. (2017). Forced asset sales and the concentration of outstanding debt: evidence from the mortgage market. *The Journal of Finance*, 72(3):1081–1118.

Fisher, L. M., Lambie-Hanson, L., and Willen, P. (2015). The role of proximity in foreclosure externalities: Evidence from condominiums. *American Economic Journal: Economic Policy*, 7(1):119–40.

Fung, R. and Lee, M. (1999). Ec-trust (trust in electronic commerce): exploring the antecedent factors.

Gao, M. and Huang, J. (2020). Informing the market: The effect of modern information technologies on information production. *The Review of Financial Studies*, 33(4):1367–1411.

Gerardi, K., Rosenblatt, E., Willen, P. S., and Yao, V. (2015). Foreclosure externalities: New evidence. *Journal of Urban Economics*, 87:42–56.

Ghent, A. C. and Kudlyak, M. (2011). Recourse and residential mortgage default: evidence from us states. *The Review of Financial Studies*, 24(9):3139–3186.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Gurley, J. G. and Shaw, E. S. (1960). Money in a theory of finance. Technical report.

Harding, J. P., Rosenblatt, E., and Yao, V. W. (2009). The contagion effect of foreclosed properties. *Journal of Urban Economics*, 66(3):164–178.

Harding, J. P., Rosenblatt, E., and Yao, V. W. (2012). The foreclosure discount: Myth or reality? *Journal of Urban Economics*, 71(2):204–218.

Hendershott, T., Jones, C. M., and Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of finance*, 66(1):1–33.

Ihlanfeldt, K. and Mayock, T. (2015). Foreclosures and local government budgets. *Regional Science and Urban Economics*, 53:135–147.

Immergluck, D. and Smith, G. (2006). The external costs of foreclosure: The impact of single-family mortgage foreclosures on property values. *Housing Policy Debate*, 17(1):57–79.

Jack, W. and Suri, T. (2014). Risk sharing and transactions costs: Evidence from kenya's mobile money revolution. *American Economic Review*, 104(1):183–223.

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the south indian fisheries sector. *The quarterly journal of economics*, 122(3):879–924.

Jiang, W. (2017). Have instrumental variables brought us closer to the truth. *The Review of Corporate Finance Studies*, 6(2):127–140.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of political economy*, 105(2):211–248.

Krishna, V. (2009). *Auction theory*. Academic press.

Lambie-Hanson, L. (2015). When does delinquency result in neglect? mortgage distress and property maintenance. *Journal of Urban Economics*, 90:1–16.

Lin, Z., Rosenblatt, E., and Yao, V. W. (2009). Spillover effects of foreclosures on neighborhood property values. *The Journal of Real Estate Finance and Economics*, 38(4):387–407.

Loutskina, E. (2011). The role of securitization in bank liquidity and funding management. *Journal of Financial Economics*, 100(3):663–684.

Loutskina, E. and Strahan, P. E. (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *The Journal of Finance*, 64(2):861–889.

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of financial Markets*, 16(4):712–740.

Meyer, D. J. (1993). First price auctions with entry: An experimental investigation. *The Quarterly Review of Economics and Finance*, 33(2):107–122.

Mian, A., Sufi, A., and Trebbi, F. (2015). Foreclosures, house prices, and the real economy. *The Journal of Finance*, 70(6):2587–2634.

Milgrom, P. R. and Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica: Journal of the Econometric Society*, pages 1089–1122.

Niedermayer, A., Shneyerov, A., and Xu, P. (2015). Foreclosure auctions. Technical report, SFB/TR 15 Discussion Paper.

O'Hara, M. (2015). High frequency market microstructure. *Journal of Financial Economics*, 116(2):257–270.

Pence, K. M. (2006). Foreclosing on opportunity: State laws and mortgage credit. *Review of Economics and Statistics*, 88(1):177–182.

Pulvino, T. C. (1998). Do asset fire sales exist? an empirical investigation of commercial aircraft transactions. *The Journal of Finance*, 53(3):939–978.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance*, 47(4):1343–1366.

Van den Heuvel, S. J. (2008). The welfare cost of bank capital requirements. *Journal of Monetary Economics*, 55(2):298–320.

Wang, J. C. (2018). Technology, the nature of information, and fintech marketplace lending. *Federal Reserve Bank of Boston Research Paper Series Current Policy Perspectives Paper*, (18-3).

Wyld, D. C. (2005). Government liquidation: How online auctions will replace bob's army-navy store. *Journal of Internet commerce*, 4(4):41–58.