Electronic Foreclosures

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Abstract

This paper investigates how auction bidding formats affect U.S. mortgage foreclosure sales. Exploiting a staggered adoption of electronic bidding across adjoined counties in a "stacked" difference-in-differences design, I show that foreclosure auction success increases by 27%, and price discounts contract by 42%. The effects are stronger in areas with more remote courthouses, and for properties in better conditions. Buyer composition of electronic foreclosure auctions shifts towards local non-professionals, who are less likely to buy-to-rent and flip acquired properties ex-post. This evidence suggests that technological modernizations in real estate markets can lead to better matching, deepen liquidity and foster financial inclusion.

Keywords: Electronic marketplace, Online auction, Mortgage foreclosures, Credit market;

JEL: G21; O33; D44;

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1 Introduction

Frictions in search markets can generate poor buyer-seller matches and inefficiently suffocate asset prices. One source of mismatching is the presence of trade costs, such as buyer transport expenses and time spent reaching the marketplace, which constrain asset demand to a small pool of bidders. Additionally, in the case of forced sales, the best-suited buyer is unlikely to be readily available within a short time to bid for the asset (Shleifer and Vishny, 1992). Trade frictions thus penalize sellers with price discounts, and could lead to market segmentation, underinvestment, and resource misallocation (Gurley and Shaw, 1960; Diamond, 1982; Allen and Santomero, 1997).

I study how relaxing these frictions affects trade outcomes using forced liquidations of U.S. real estate as a laboratory. Since the American Revolution, foreclosure sales of mortgaged properties have consisted of a public auction conducted at the premises of the county courthouse. Typically without much bidding competition, lenders end up purchasing the foreclosed property, incurring substantial holding costs afterwards.[1] Furthermore, each foreclosed home that is left vacant and in deterioration creates negative physical externalities on the value of neighboring properties (Harding et al., 2009; Campbell et al., 2011). As these visual spillovers go beyond simple supply effects, economists advocate government intervention. To achieve the largest social value policymakers should streamline the foreclosure process, rather than abolishing the foreclosure remedy at all (Fisher et al., 2015; Gerardi et al., 2015).

This paper takes a micro approach to empirically estimate the effects of one such policy. In the summer of 2008, Florida has been the first state in the U.S. modifying its statute and allowing its courts to switch from in-person open outcry to electronic bidding when conducting their foreclosure auctions.[2] Economic theory suggests that, when sellers are price-takers, online auctions reduce buyer transaction costs and facil-

[1]Lender's total costs of ownership begin after no third parties buy at the foreclosure auction. Real Estate Owned (REO) asset 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.

[2]Florida and Ohio are the only two states in the U.S. conducting electronic foreclosure auctions. However, most counties in Ohio adopted the state policy (Bill 390) during the Covid-19 pandemic, making any empirical assessment of electronic auctions in this state rather problematic.

itate bidder participation, pushing final asset prices up (Klein, 1997; Lee, 1998). The *buyer externality* can be an important benefit of online marketplaces given the negative price spillovers and feedback loops associated with asset liquidations (Kiyotaki and Moore, 1997; Asquith et al., 1994; Brunnermeier and Pedersen, 2009).

By making buyer participation easier and widening trade, the findings of this paper suggest that electronic bidding considerably benefits lenders with mitigated liquidation discounts and quicker sales, gaining from a substantial reduction in asset ownership expenses. This leads to a reallocation of resources from the bank sector, who is holding troubled assets, to the household sector, who is buying them. Considering the opportunity cost of a vacant property, brokerage sale commissions, and inventory costs, higher success at the foreclosure auction leads to an aggregate welfare gain. In addition, the improved sale technology indirectly should assist defaulting borrowers by receiving smaller deficiency judgements, as well as neighborhoods and the community therein by absorbing lower externalities.

An information channel contributes to the increased liquidity and redistributed welfare, as buyers of electronic foreclosures are more likely to come from areas closer to the foreclosed property with respect to in-person auctions. By means of electronic bidding, informed local buyers can better assimilate information, start bidding more precisely, and acquire properties as their primary residences, as suggested by fewer volume buyers and fewer properties flipped ex-post. Moreover, winners of electronic foreclosure auctions are less likely to be professional investors, who generally are used to buy-to-rent and care exclusively about financial returns. Given the highly segmented setting of the housing market, a shift from non-local professionals to local non-professional comes as no surprise.

The empirical strategy employed relies on the passage of a state bill in Florida which counties embraced at different points in time. Anecdotal evidence suggests the policy adoption was primarily meant to eliminate labor costs, paper-based processes, unforeseen events (blizzards, fire drills, power outages, etc.) and disruptions for political or personal reasons. These arguments are associated with operational inefficiencies of traditional live auctions, providing a clean setting to study the impact of technology change. Nevertheless, concerns about reverse causality are plausible. If the adoption was the response to poor foreclosure outcomes in the county, OLS estimates would bias the true effects of online auctions. In an instrumental variable (IV) approach, the court backlog is used to exploit the "good variation" of the shock (Besley and Case, 2000). The idea is that when court departments expect not to "keep up" with their caseload, it is more convenient to decentralize and automatize their foreclosure auctions. The exclusion restriction is unlikely to be violated since future court pressure (resulting from, e.g., risky lending) is unrelated to past auction participation. A corrective IV exercise confirms the positive effects of electronic bidding. Also, it is important to notice that $\hat{\beta}^{DD}_{IV}$ is only 1.5-2 times larger than $\hat{\beta}^{DD}_{OLS}$, suggesting that the instrument is not weak and that the OLS estimate slightly understate the true effect (Jiang, 2017).

The interstate difference-in-differences (DD) design of the present study compares electronic foreclosure areas ("treated") to adjoined outcry bid regions ("control") using novel tax roll data over the years 2009 to 2019 collected from the Florida Department of Revenue. Property appraisers do record transfers and their prices also when auctioned properties go back to lenders (Anenberg and Kung, 2014; Chinloy et al., 2017). Although these non-arms' length transactions are bookkeeping entries with no cash implications, close duplicates per parcel are useful to classify auction outcomes.[3] In addition, I exploit the county assessor's opinion of the market value of each residential property, which arguably considers all its tangible and intangible conditions. This allows to separate "proxy" effects out and overcome common measurement issues the literature has documented so far. Instead of using hedonic models or repeat sales estimation, the foreclosure discount is simply calculated by comparing the final price of each foreclosure acquisition with its own market value county appraisers assessed at the end of the previous year.

All specifications control for county border by month fixed effects, and granular geographical (e.g., zip-code or census tract) fixed effects, so that identification is net

[3]To validate our procedure, I use the actual auction outcomes from the platform which covers only treated counties in the time period after the shock. False positive-negative rates range from 9% to 12%, depending on the types of transfers taken into account in the tax roll data.

of unobservable regional time trends and neighborhood characteristics. The economic significance of the various point estimates is non-negligible. Electronic foreclosures lead to a 5 percentage points increase in auction success and a 3 percentage points decline in foreclosure auction discount. Comparing these estimates with the unconditional mean of the variables, the effects represent a 27% increase and a 42% decrease, respectively. A simple back-of-the-envelope calculation, including avoided brokerage fees and freed up bank capital, estimates a large positive economic value (averaging $35 million) associated with electronic bidding of foreclosure auctions.

I conduct additional exercises exploring heterogeneous effects to further our understanding of the results. Largest beneficial effects are found in months with higher foreclosure rates, in counties with more remote courthouses, and for properties that are more distant from the courthouse. Furthermore, the electronic bidding benefits increase in the quality of the auctioned property, suggesting that the reduction in buyer search costs (e.g., enabling the comparison of different product offerings) is an important effect of electronic marketplaces (Bakos, 1997, 1998). All in all, this evidence is consistent with an informational channel (i.e., highest value users) associated with asset illiquidity (Shleifer and Vishny, 1992). REO sales slightly worsen following the technology change, as REO discounts increase by 1 percentage point, but the estimates have poor statistical power. Regardless of the price discount, lenders manage to sell REO assets faster, reducing then vacancy rates in the neighborhood. Therefore, it is legitimate to conclude that the negative REO effects do not offset the positive auction outcomes.

This study contributes to several strands of literature. First, the advent of electronic marketplaces has reduced buyer search costs and inefficiencies caused by it (Bakos, 1997, 1998). When sellers have pricing power, online products can be cheaper (Brown and Goolsbee, 2002; Morton et al., 2001; Brynjolfsson and Smith, 2000) or more expensive (Bailey, 1998; Lee, 1998) than when sold offline. The setting of this paper abstracts from seller pricing strategies in both the offline and online versions of the market. Once a property is scheduled for foreclosure, in fact, lenders have little or no control over the legally structured and lengthy process that brings to the auction.[4] When assets are illiquid and have a low degree of substitutability (such as real estate), the buyer externality of online platforms facilitates trade and increases prices.

Second, the illiquidity component of asset sales is present in several markets. In the real estate context, although papers exhibit large variation in terms of definitions and estimates, all recognize the existence of a foreclosure price discount (e.g., Campbell et al., 2011; Anenberg and Kung, 2014). I show that one of its determinants is the restricted pool of buyers. Most papers focus on either REO sales or (less frequently) on foreclosure auctions. Instead, this article investigates both alternatives of foreclosure sales together, which further our understanding of their functioning, and the relationship between the two. Because of deteriorated physical effects, 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). One of the policy implications of this paper is that technological improvements at the foreclosure auction stage can relief lenders from idle capital and neighborhoods from negative social externalities.

Finally, integrated markets benefit from the absence of barriers to trade and arbitrage opportunities. Arbitrage is necessary to restore market efficiency, as it helps bringing prices to fundamental values (Sharpe et al., 1999). The applied evidence in this paper is consistent with the price convergence theory. Remote bidding in foreclosure auctions aggregates liquidity from different market players, smoothing out price fluctuations to county- or city-specific shocks (Hallwood and MacDonald, 2000; Lafrance et al., 2002), provides diversification benefits for external liquidity providers and increases within-market ownership diversity.

The paper continues as follows. Section 2 provides a summary of the U.S. foreclosure laws and formulates the hypotheses for empirical testing. Section 3 describes the foreclosure auction data used in the analysis and section 4 presents the results.

[4] A robustness exercise confirms this idea testing whether the electronic bidding effect has a different impact on properties foreclosed by governmental agencies (such as Fannie Mae or Freddie Mac). The insignificant results are consistent with an unanticipated shock on the demand side.

Finally, section 5 concludes.

2 Institutional Background and Hypotheses

This section describes U.S. foreclosure laws and the auction format policy enacted in Florida in 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. after three months of missed mortgage payments, the lender mails a notice of default to the borrower. While a property repossession can be expedited and directly handled by a trustee in power-of-sale states, lenders have to file a lawsuit to foreclose to the court in judicial states (which include Florida). County clerks then check evidence of default and outstanding debt amount before approving a final judgement amount and setting 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).[5] Each county court requires publication of the foreclosure property advertisement in a local legal newspaper several (e.g., two or three) weeks before the scheduled auction.[6] During the pre-auction period, although a "for sale" sign is posted on the property, potential bidders by law cannot inspect inside property conditions.

At the auction, there is no particular restriction on bidders, except for in-advance registration and deposit (e.g., 5% of the expected winning bid). The design of U.S. foreclosure auctions is an ascending bid mechanism which, relative to sealed bidding, is known to provide more information to bidders, increase efficiency and mitigate the

[5]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).

[6]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.

winner's curse (Milgrom and Weber, 1982). Foreclosure auctions are fixed reserve: lenders set in advance a reservation price ("credit bid"), which can either be disclosed to bidders in advance or maintained hidden. The transaction must be a cash sale and properties are sold "as is".

Traditionally, bidders shall 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., airfare and lodging, transport services, 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 and 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) and limit the number of potential bidders who can attend. Bid-rigging or collusion are not unheard of at physical auctions, either.

At the foreclosure auction stage, there are three possible outcomes. In two cases the auction can be successful: if any third party cash bid exceeds the judgment amount (lender's claims and associated legal expenses), any surplus balance left goes to the defaulting borrower; instead, when the final bid is below the judgement amount, lenders may however accept the offer but the borrower becomes liable to pay the deficit ("deficiency judgement").[7] 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 frequent outcome in the U.S., where most of the time the foreclosing lender buys back the property.[8]

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 physical conditions deteriorate over time, but also legal expenses can be substantial. For each REO

[7] Lenders have the option to sue for the remaining balance, but rarely do that (Burkhart, 2017).

[8] 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.

property, 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 REO for a long time (but no more than five years by regulation), 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 and social mechanisms, determine a price. Starting in the 1990s, the Web 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 allows to approach an extended audience, even for specialized assets, fostering the required asset liquidity in impaired markets. 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 commuting expenses and time which can be used to prepare a better bidding strategy. This yields the following predictions:

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

Prediction 2 *Foreclosed properties trade at smaller price discounts if sold through electronic auctions than if the bidding is made in-person.*

Prediction 1 and 2 refer to the marginal effect of online bidding with respect to physical bidding, and are related to the intensive and extensive margins of auction participation. Lower transaction costs permit even the marginal (e.g., spatially or financially constrained) bidder to break-even, enlarging the pool of buyers. Moreover, this reduction of trade costs positively affects the bidder's reservation price and, thus, increases 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. It follows from predictions 1 and 2 that higher participation leads to more aggressive bidding and higher final sale prices. In search markets, the change in buying-behavior is one of the direct impacts of the Internet on trade outcomes of heterogeneous goods (Bakos, 1997, 1998).[9]

2.3 Empirical Strategy

Foreclosure auctions offer an ideal setting for empirical identification as the sale environment is subject to regulated rules of court supervision. It is publicly advertised in advance and constrained to a pre-determined short time window. Moreover, there are no negotiation frictions between agents, user experience does not play a role,[10] and sellers have limited or no influence on the outcome.[11]

The online effect could be estimated by comparing real estate foreclosed and auctioned in states with electronic bidding to other states where foreclosed properties get auctioned physically with the bid outcry method. However, this estimation strategy would likely be biased as different foreclosure laws apply, mortgage markets differ, and properties have different unobservable characteristics. To address these issues, I focus on a single state and exploit a law approved in Florida in the summer of 2008.

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. states, clerks of Florida circuit courts have traditionally conducted foreclosure sales by inefficient and expensive in-person

[9] Seller's search strategies change as well in online marketplaces, as the seller's opportunity cost, that is turning the high bid down and waiting for a better bid in a subsequent auction, decreases (Kuruzovich et al., 2010). The U.S. foreclosure setting permits to depart from any seller effects, as lenders cannot relist by law an unsuccessful auction and cannot use other sale platforms.

[10] 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.

[11] Due to deterioration, management and legal costs, lenders have ex-ante incentives to 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.

auctions. While facing the foreclosure wave that was engulfing the state legal system, on 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, removing the obligation to physically go to the courthouse.

Importantly, the proposed technology is not mandatory. In fact, county courts took up the policy at different points in time (see Figure 1). In ten years since the policy enactment date, 29 out of 67 counties adopted this bidding technology. All electronic counties (except for Palm Beach) use *realauction.com*, a private online sale platform.[12] Since the rest of counties are non-adopters, identification of the treatment effect comes not only from *whether* treatment was ever assigned but also from *when* treatment was assigned. 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 (DD) design. This matching strategy is based on relatively small geographical areas to ensure that real estate assets are exposed to similar (regional) conditions.

A staggered DD makes this empirical method a quasi-experimental technique that addresses potential divergences in market conditions and contemporaneous laws. To circumvent the heterogeneity problems of the twoway fixed-effects DD estimator (Goodman-Bacon, 2021), I follow Cengiz et al. (2019) 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 relative time. The stacking process consists of grouping treated counties with both their “never-treated” counties and (if any) “late-treated” counties among the set of neighboring ones.

Among the set of never-treated counties, Franklin, Taylor, Dixie, Lafayette, Suwan-

[12] The fact that the auction bidding format is not a seller decision variable makes the electronic technology an exogenous treatment. This allows to study the effect of the electronic bidding on foreclosure outcomes.

nee Hamilton, and Madison do not adjoin any treated county and, thus, are excluded from the analysis. Moreover, 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 DD 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.[13]

The DD regression equation takes the following form:

$$FclOutcome_{i,c,t} = \beta Treated_c \times Post_t + \gamma Treated_c + X_{i,c,t} + \alpha_{bt,n} + \varepsilon_{i,c,t} \quad (1)$$

where $FclOutcome_{i,c,t}$ 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 auction success and property discount. The $Treated_c$ vector takes value 1 if a county c in a county border cohort b receives the technology treatment, and 0 otherwise. $Post_t$ is a dummy variable taking value 1 in all months t after a county c in a group b receives the treatment, and 0 before that. The standalone $Post_t$ coefficient is absorbed by time fixed effects. The vector of residential property characteristics is denoted by $X_{i,c,t}$, and includes property age, size (total area of all floors), number of residential units and appraised structure quality. Finally, $\alpha_{bt,n}$ is a set of fixed effects at county border times month and census tract n level, a small geographic area in the U.S. with a population of approximately 2,000-4,000 persons. The stacked cohort (county border) fixed effects are crucial for this specific DD design and is the only feature that differ from the standard DD estimand. Conditional on the parallel trend assumption, the coefficient β on the interaction term $Treated_c \times Post_t$ captures the effect of the online bidding. Standard errors are clustered at county (policy) level, accounting for the possibility that auction outcomes may be correlated within

[13] 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 and it is not in their interest to overbid the judgement amount when borrowers are underwater.

a county.

3 Data

The study of foreclosure outcomes requires to observe the characteristics and location of foreclosed properties, as well as the transaction price and sale means of the transfers. I use comprehensive data from the Florida Department of Revenue to accomplish this. For tax purposes, this state agency collects annual assessment rolls of all the real properties present in a county in Florida. The assessment rolls are publicly available and include information on each parcel, such as the owner's name and residence place, property characteristics, as well as its market value. By law, members of the Property Appraiser's Office shall inspect all property in the county at most once every five years. Though in the data sample property inspections occur every 3.5 years, the assessed value is observed on an annual basis due to extrapolation.

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 (3-rd party acquisition) from a REO sale. However, a simple and well-founded classification rule for auction success exists: property appraisers do record transfers and prices also when auctioned properties go back to lenders (Anenberg and Kung, 2014; Chinloy et al., 2017). Although these are bookkeeping entries with no cash implications, researchers can use them to identify auction outcomes. I classify a 3rd-party auction sale if a disqualified transfer in month t is not followed by any other disqualified transfers in the subsequent four years. The results are robust to alternative choices of this time window.[14] After this classification, 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 (10%) false positive-negative rate.

[14] 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.

I focus on single-family residential properties with at least one disqualified sale over the sample period. This leaves about 5 million parcel-level observations per year. In the price analysis, I exclude observations with sale prices that deviate by more than 50% from their appraised values (Donner, 2020). 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 if any changes in lenders' incentives to foreclose or to accept bids differently before and after the technology shock could materialize immediately. This is unlikely to be a persistent bias in such a short estimation window, as foreclosures are structured and lengthy processes.[15] Regarding lenders' behavior at the auction, there is no reason why lenders should reject good bids, as REO assets are very costly to maintain. Therefore the likelihood that lenders anticipate and manipulate foreclosed auctions in our context is rather small.[16]

Table 1 shows the summary statistics of the variables. Panel A shows that lenders manage to sell to third-party bidders 18% of the 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 (Clauretie and Daneshvary, 2009; Chinloy et al., 2017; Donner, 2020). Furthermore, an 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 REO properties (unsuccessful auctions) sell at about half of the auction discount, lenders do incur additional holding costs when selling an REO asset, as described above.

[Table 1 here]

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

[16] 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/).

As expected, there is considerable variations in the variables across counties and over time. Panel B shows the changes in auction outcomes and in the property characteristics before and after the electronic bidding shock. Comparing treated and control counties, we can already intuitively see the effect of the policy: treated counties pass 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 or the endogenous part of the policy implementation, an issue I will return to below in the parallel trend test and in the IV 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, reinforcing 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 of the dynamics of the main dependent variables of interest. Figure 2 plots the monthly foreclosure auction success rate, defined as the fraction of 3-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 in the two time windows, border groups with a pre-policy window shorter than 15 months are excluded from these averages.

[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 policy timing. Nevertheless, the fact that both lines move in the same direction mitigates (at least partially) 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. Though this is a crude descriptive dynamics of the main variables, it highlights the potential for electronic bidding to have a significant impact on foreclosure auction success.

Table 2 tests hypothesis 1 more rigorously by means of OLS regressions. Controlling for time-varying covariates, omitted variable bias can be avoided, and the precision of DD estimate improved. The coefficients are estimated through a linear probability model (LPM) and follow the regression model of equation 1. All specifications include county border times month fixed effects which saturate the $Post_t$ dummy. Column 1 shows that the dependent variable $AucSucc_{i,c,t}$ is positively affected by the electronic bidding technology. The DD interaction coefficient $Treated_c \times Post_t$ measures 0.0542 and statistically differs from zero. In column 2, characteristics of the auctioned property are added as 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 altered. The fact that the results are not driven by the inclusion of controls suggests that the treatment does not have 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 slightly in magnitude. Finally column 4 and 5 add property zip code and census tract fixed effects, respectively, and in both cases the interaction coefficient remains statistically significant. The estimated effect of electronic bidding is relatively large (27%) when compared to the unconditional mean of auction success (18.09%).

[Table 2 here]

The time breakdown of the point estimate constitutes a crucial part of any DD 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 not violated. The comparable dynamics between the two groups in the pre-treatment period points largely in favor of the crucial 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. The fact that pre-policy event-time indicators are negative (but not statistically significant) may suggest that the policy adoption depends on poor foreclosure outcomes. In the next section, an instrumental variable attempts to take care of this remaining endogeneity.

4.2 Foreclosure auction discount

The extensive margins of electronic bidding is an important result. Table 2 suggests that 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 flooding banks' balance sheets and degrading a neighborhood conditions. Another important question is to investigate what happens to the final price of third-party-acquired properties. 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 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 move in the same direction in the period before the policy adoption. At t=0, the average discount in treated counties drop more than in similar control counties. The exercise in Table 3 tests this hypothesis 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 final price (winning bid) divided by 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 the specification in 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 more stringent fixed effect (census tract 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 has reduced the auction foreclosure discount by slightly more than 3%. Therefore, also at the intensive margins, electronic bidding improves foreclosure auctions, as the discount lenders receive shrink substantially (42% of the average discount). This important for borrowers receiving foreclosure, as they are subject to smaller deficiency judgements. Moreover, these results may have implications for non-foreclosed properties as well, due to lower negative price spillovers. Nevertheless, this result will not enter in the welfare calculation as the smaller price discounts are offset by someone's else paying a higher price (zero sum).

In the event study plot in Figure 5 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.[17]

[Figure 5 here]

4.3 Instrumental Variable approach

One econometric issue that may complicate the estimation of treatment effects is when the group who would gain the most from a policy are most likely to seek it. If that was the case, the evaluation of the effect of the policy is subject to biases. One appropriate solution is to control for the forces leading to the decision to treat, by modeling them as a function of the pre-treatment aggregate characteristics. These pre-treatment factors can then be used as instruments to identify the treatment incidence (Besley and Case, 2000).

We exploit foreclosure and non-foreclosure legal filings court receives to predict their technology adoption decision. The idea is that when the number of foreclosures f (or more generally workload) courts foresee becomes large enough, then it is more

[17]The fact that the electronic bidding technology helps bringing distressed asset prices back to intrinsic value should be reflected across areas. Consistently, the monthly differences in R^2 between treated and control counties increases after the shock (results available upon request).

convenient to switch to online auctions. It is fair assuming 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, it exists a workload level f^* after 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 in a month (Z) do not directly affect the outcome of foreclosure auctions in previous months (Y).

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 border group, 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 (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). In other words, expected workload seems to be a good predictor of the technology take-up. Also, treated and control units of late adopting groups (larger values on the x-axis) face fewer backlog on average. This may reflect the time-dependent foreclosure scenarios taking place in Florida. Table 4 shows the results of the instrumental variable estimation. The bottom panel presents the first stage coefficients. In the same spirit of Duflo

(2001) methodology, interaction terms between $Post_t$ and foreclosure ($Fcl_{c,t\in(-12.0)}$) filings or non-foreclosure cases ($NonFcl_{c,t\in(-12.0)}$), averaged over the year before the treatment date, instrument the endogenous $Treated_c \times Post_t$. [18]

[Table 4 here]

As expected, the coefficients are positive and statistically significant, suggesting that more exposed counties within a border group are more likely to adopt the policy. In both the auction success model (column 1 and 2) and the auction discount model (3 and 4), the filings variables pass the weak 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 OLS coefficients of the baseline model (the last columns of table 2 and table 3). This is consistent with the idea that larger current backlog predicts more future foreclosures, which hamper auction success and amplifies price discounts through a supply effect.

4.4 Channels

In this section, I explore the channels driving the positive effects of electronic bidding. Trade frictions could play a role through marketplace access costs, financial and capacity constraints of prospective bidders, or both. Taking the specification in the last column of Table 2, the regression coefficients displayed in Table 5 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 5 here]

[18] 2SLS results are robust to different time windows over which legal filings are averaged.

Column 1 investigates the 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 main cities in the region and that is easily reachable by more people. 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 include the distance (in thousand miles) between the foreclosed property and the court. In this case, the estimate is again statistically significant and positive. Overall, these results clearly show larger gains of electronic bidding in situations with more difficult accessibility.

Column 3 seeks to understand whether the electronic bidding effect could relief fire sales. This time 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 suggest that larger trade gains are found in more competitive periods of time. The electronic platform attracts more buyers aggregating and distributing liquidity among properties. Finally, column 4 tests matching allocation. Good quality assets are easier to sell, but trade frictions (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 general 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 (data unavailable). This evidence is consistent with new bidders with different preferences joining the bidding process.[19] The next section explores final buyers more in depth.

[19]This is also consistent with the theory proposed in Bakos (1997, 1998), which highlights the reduction in buyer search costs (e.g., enabling the comparison of different product offerings) as the primary effect of electronic marketplaces.

4.5 Auction Buyers

To further the understanding of the source of frictions and how welfare gains redistribute, it is important to study final users of acquired properties at the auction. Therefore, I examine how the composition of the pool of auction buyers 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 foreclosure auction owner with the previous year sample of owners of non-foreclosed properties to gather her previous residence place and real estate portfolio volume. To minimize the case in which persons have the same name, I exclude owners with multiple residences in a year. 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 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 are excluded due to missing information. The resulting sample for this analysis is reduced.

[Table 6 here]

Table 6 presents the results of the DD regression on auction buyers 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. 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 more precisely. 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 c, respectively. In both cases, the interaction coefficient is negative. Electronic bidding has reduced the distance (costs) a buyer should handle to bid and acquire a foreclosed property at the auction.

Next, in column 4 I consider 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.[20] The DD 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 becomes simply not an attractive investment opportunity anymore. Finally, column 6 shows that buyers of electronic auctions maintain the property as the main residence and flip it less often in subsequent years.

4.6 REO sales

Having determined that the electronic bidding technology favors auction transactions and mitigate auction discounts, I now proceed to test its effects on unsuccessful auctions. If the final bid is not deemed suitable for the foreclosing lender, the title of the foreclosed property goes back to its balance sheet in the form of Real Estate Owned (REO) asset. 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 amplified. Table 7 explores this question by means of

[20] 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.

OLS regressions and survival analyses.

[Table 7 here]

Specifications in Table 7 shares 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 measures 1.48%, 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 very low probability of success. Therefore, in column 2, I exclude from the sample REO properties that receive a low predicted score (below 10th percentile) from the 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. 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.

The last two columns of Table 7 investigates the time on market of foreclosure foreclosed properties. 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 with duration models, as using regression techniques involves problems (the dependent variables can change during the period). Column 5 estimates a Cox proportional hazards model via maximum likelihood. The disadvantage is that this type of estimation has 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. This suggests that overall lenders manage to sell foreclosures quicker.

4.7 Robustness Tests

This section tests the robustness of inferences. To ensure that the estimation process is not capturing any size effect of treated counties, column 1 of Table 8 drops 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 part of the sample for this exercise. 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 DD estimation, this placebo exercises confirms that the control group did not experienced any change in outcome. Relatedly, to study spillover effects such as the possibility that buyers of control areas get attracted from the treated region, column 2 excludes parcels 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 3 excludes border cohorts with counties that received the treatment too early (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 4 checks whether estimation is contaminated by comparisons of late versus earlier treated counties. This does not seem to be an issue, as the main coefficient of interest is positive and statistically significant. Column 5 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 results are confirmed. Finally, column 6 tests whether incentives from the supply side play a role. The triple interaction between the electronic bidding effect and an indicator for Government Agency (including HUD, Fannie Mae, and Freddy Mac) loans is not statistically significant, confirming that over such a short estimation window the foreclosure process is difficult to manipulate.

4.8 Welfare

The measurement of welfare is centrally important to the economic analysis of a policy. In this case, we have seen that the technology policy has improved the auction stage of residential foreclosures in Florida, relieving investors with fewer REOs. Without taking into account secondary effects (e.g., deficiency judgements, externalities), the primary surplus is generated through faster allocation of unusable assets taken away from imperfect users (lenders) and assigned to high value users (third-party buyers).

In the data, the average REOs time on the market is 7.5 months. Looking at table 2, electronic bidding has decreased the number of REOs by **5%**. 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.[21] The welfare analysis of the electronic bidding effect can be split into three components: opportunity cost, intermediation, and regulation.

1. Opportunity cost (empty home): the first piece 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. The average monthly rent of a two bedroom apartment is \$947 (www.rentdata.org). The monthly value is: $\mathbf{5\%} \times \$947 \times 55,000/12 months = \$217,000$

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%.[22] These include maintenance expenses, tax and insurance on the property, and reselling brokerage fees. From a social welfare perspective, the first two components are "zero sum", as buyers will have to pay for them anyway. The latter is a welfare gain, assuming that realtors' fees correspond to the actual servicing expenses

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

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

(driving, electricity, document stamps, etc.). 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: $\mathbf{5\%} \times 5.5\% \times \$196,000 \times 55,000/12months = \$2.5M$

3. Opportunity cost (bank capital): 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 constraint is 8%, the additional capital banks have to hold to back REOs is 4%. 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 8%, the welfare value is: $\mathbf{5\%} \times 4\% \times \$196,000 \times 55,000/12 \times (1 + 8\%/12months) = \$1.8M$.

Summing up these pieces together, a lower bound for the total welfare associated with this policy is $(\$217,000 + \$2.5M + \$1.8M) \times 7.5months = \$33.9M$. This can be considered as a lower bound for the welfare calculation as participation costs (e.g., time, effort, fuel) of participants in the auction are likely lower.

5 Conclusion

This study uses Florida real property roll tax data together with appraisals of residential properties sold through foreclosure to estimate the effect of electronic bidding on foreclosure outcomes. Foreclosure auction sales and REO sales are classified based on the frequency of distressed sales in the real property roll. Exploiting the staggered electronic bidding adoption of several counties over a 3-year time window, a difference-in-differences design estimates an increase on auction success by 28% and a decline on auction discount by 38%, on average. The results are robust to different samples and placebo tests.

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 and it is clean from any supply effects over such a short estimation window.

I also analyze the REO market. 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. Taken together, the welfare improvement is substantial, accounting for at least \$35M. Understanding the relation between higher foreclosure auction success and other credit supply decisions is an important avenue for future research on mortgage credit markets.

The evidence presented in this paper is consistent with the idea that the foreclosure process is flawed from a buyer perspective and that removing bidding frictions by means of technology can improve buyer-seller matching in the real estate market. Faster reallocation of risky distressed assets from the bank sector to the household sector generate substantial welfare gains.

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

	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 from FL Department of Revenue, *realauction.com* or *FLCourts.org*) and summary statistics, including the mean, standard deviation, and the main percentiles, of the variables used in the empirical analysis. Panel B compares the first moment of the main variables for the treated group and control group, before and after the shock.

Table 2: Electronic Bidding and Foreclosure Auction Success

Dep. var.: $\text{AucSucc}_{i,c,t}$	(1)	(2)	(3)	(4)	(5)
$\text{Treated}_c \times Post_t$	.0542***	.0529***	.0456**	.0503***	.0493***
	(3.04)	(3.00)	(2.23)	(2.75)	(2.78)
Treated_c	-.0469**	-.0530***			
	(-2.57)	(-3.25)			
$\text{HouseAge}_{i,c,t}$		-.00127***	-.00105***	-.000811***	-.000867***
		(-5.34)	(-4.67)	(-5.45)	(-6.17)
$\ln(\text{Size})_{i,c,t}$		-.0280***	-.0385***	-.0282***	-.0247***
		(-3.76)	(-7.79)	(-7.97)	(-8.02)
$\text{NoResUnts}_{i,c,t}$		-.00007***	.00097	.00005	-.00046
		(-9.12)	(.72)	(.06)	(-.54)
$\text{StrucQual}_{i,c,t}$		-.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	350,065
R^2	.046	.049	.063	.081	.092
adj. R^2	.044	.047	.061	.075	.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. 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. County-clustered standard errors 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.: AucDisc$_{i,c,t}$	(1)	(2)	(3)	(4)	(5)
Treated$_c$ × $Post_t$	-.0485***	-.0435***	-.0263**	-.0279*	-.0337**
	(-4.96)	(-5.06)	(-2.08)	(-1.77)	(-2.18)
Treated$_c$	.0518***	.0385***			
	(3.02)	(2.68)			
HouseAge$_{i,c,t}$		.00205***	.00193***	.00192***	.00198***
		(12.66)	(13.98)	(10.40)	(11.46)
ln(Size)$_{i,c,t}$		-.0453***	-.0295***	-.0205***	-.00903*
		(-5.76)	(-5.90)	(-4.38)	(-1.91)
NoResUnts$_{i,c,t}$		.0609***	.0495***	.0399***	.0443***
		(4.56)	(4.45)	(3.86)	(3.89)
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 the property. 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. County-clustered standard errors 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)
$\ln(\text{Filings})_{c,t\in(0;-12)}$	.387***	.399***	.519***	.498***
$\times Post_t$	(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 column 3 and 4, the dependent variable is $AucDisc_{i,c,t}$ that 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 (column 1 and 2) and non-foreclosure civil (column 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. County-clustered standard errors are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 5: Triple Difference-in-Differences

Dep. var.:	$\text{AuctSucc}_{i,c,t}$			
DDD Channel:	Remote_c (1)	c-iDist_i (2)	$\text{NoAuct}_{c,t}$ (3)	Quality_i (4)
$\text{Treated}_c \times Post_t \times Ch$	.461**	.517*	.118**	.0260**
	(2.24)	(1.80)	(2.48)	(2.40)
$\text{Treated}_c \times Post_t$	-.381**	.0426*	-.0257	.0422**
	(-2.08)	(1.77)	(-1.57)	(2.38)
$\text{HouseAge}_{i,c,t}$	-.000867***	-.000955***	-.000868***	-.000866***
	(-6.16)	(-6.03)	(-6.18)	(-6.26)
$\ln(\text{Size})_{i,c,t}$	-.0249***	-.0250***	-.0247***	-.0242***
	(-8.07)	(-7.62)	(-7.99)	(-7.92)
$\text{NoResUnts}_{i,c,t}$	-.000423	-.00086	-.00036	-.00044
	(-.50)	(-1.01)	(-.42)	(-.51)
$\text{StrucQual}_{i,c,t}$	-.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. County-clustered standard errors 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 selling the property. $Profssnal_{i,c,t}$ 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. Census tract fixed effects and border times month fixed effects are included in all specifications. County-clustered standard errors are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 7: 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. County-clustered standard errors are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Table 8: Robustness exercises

Dep. var.: $\text{AuctSucc}_{i,c,t}$	(1) Placebo	(2) Donut	(3) LateTreatm	(4) NotYetTreated	(5) WeightReg	(6) Supply
$\text{Treated}_c \times Post_t$	.00416	.0526***	.0513***	.0598***	.0452***	.0466**
	(.16)	(2.99)	(2.79)	(3.18)	(2.97)	(2.43)
$\text{HouseAge}_{i,c,t}$	-.00081***	-.00088***	-.0010***	-.0010***	-.00069***	-.00089***
	(-4.34)	(-5.90)	(-5.87)	(-7.14)	(-3.72)	(-6.34)
$\ln(\text{Size})_{i,c,t}$	-.0211***	-.0242***	-.0248***	-.0232***	-.0301***	-.0258***
	(-4.54)	(-7.66)	(-6.43)	(-6.89)	(-6.23)	(-8.11)
$\text{NoResUnts}_{i,c,t}$	.00112	-00058.	-.0023	-.00076	.00298	-.00053
	(.87)	(-.70)	(-.30)	(-.98)	(.27)	(-.61)
$\text{StrucQual}_{i,c,t}$	.00435	.00089	-.00177	-.00151	-.00151	.00126
	(1.18)	(.47)	(-.74)	(-.80)	(-.58)	(-.69)
$\text{Treat}_c \times Post_t \times GovAg_{i,c,t}$						.0763
						(1.43)
Border×Mnth FE	✓	✓	✓	✓	✓	✓
Geog FE	n	n	n	n	n	n
# of Observations	171,702	328,229	249,810	305,721	249,902	350,065
R^2	.088	.095	.093	.094	.087	.095
adj. R^2	.072	.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 excludes zip codes that less than five miles away from a county border. In column 3, the sample is restricted to county borders with pre-shock window longer than 16 months. Column 4 drops "not-yet-treated" counties from the control group. Column 5 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 6 adds the dummy $GovtAg_{i,c,t}$ taking value 1 if the foreclosing lender is a Government agency (including HUD, Fannie Mae, and Freddy Mac), and zero otherwise, to the baseline model. $Post_t$ 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. County-clustered standard errors are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively.

Figures

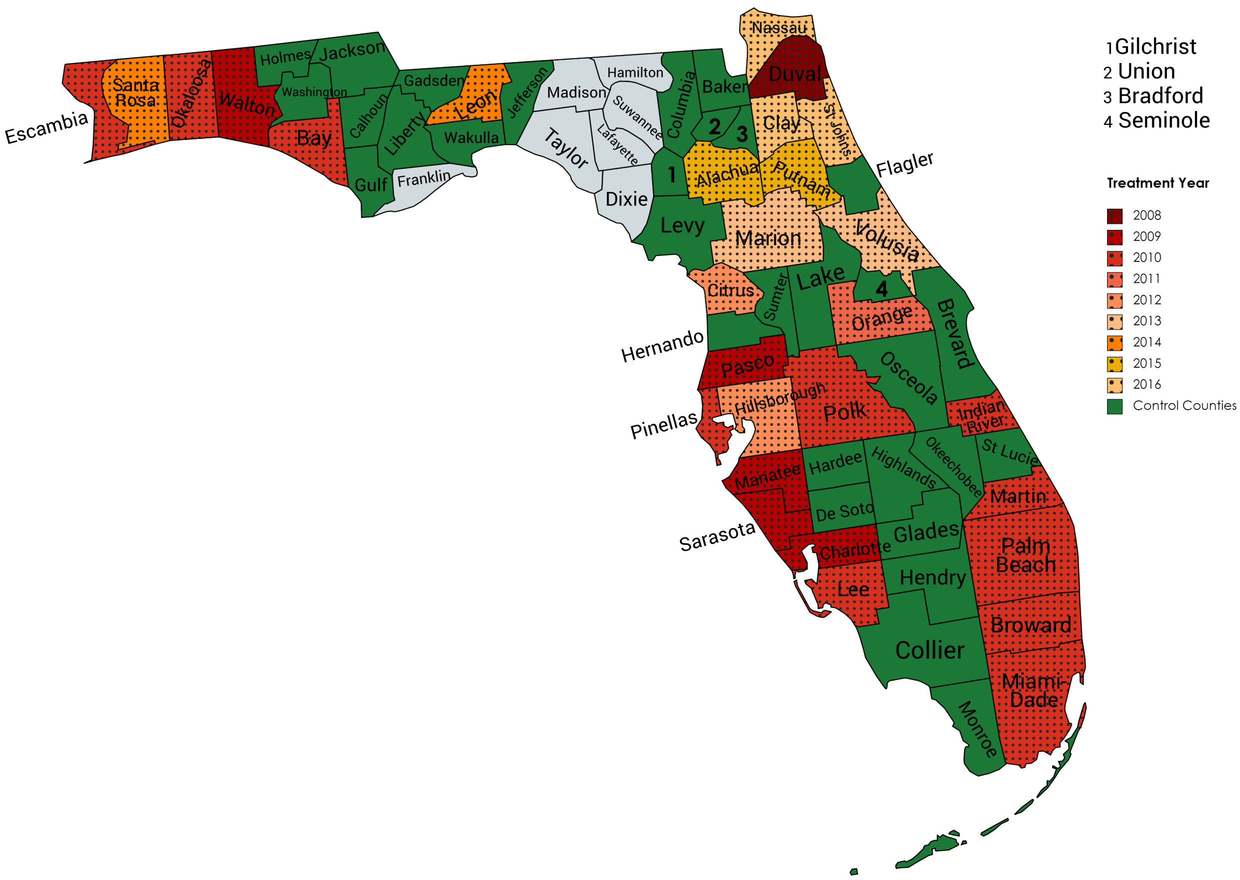


Figure 1: Treatment incidence and timing. This figure shows the year in which Florida counties adopted (dotted) the online bidding technology, those that never adopt but adjoin adopters (green) and those that never adopt and do not adjoin adopters (light blue). Adoption decisions are considered up to, 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. The values are averaged within treated (blue) counties and control (red) counties per month.

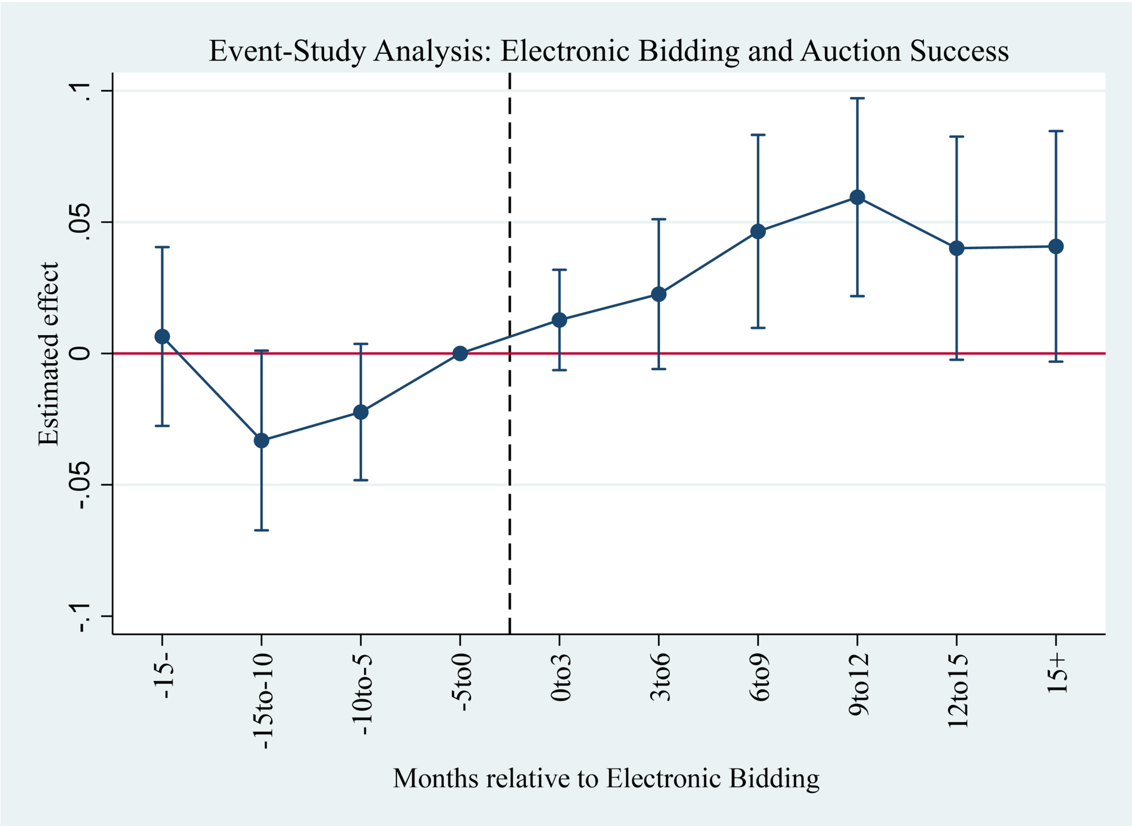


Figure 3: Event study estimates of electronic bidding on foreclosure auction success. The point estimates are based on time indicators replacing the dummy $Post_t$ in model 1.

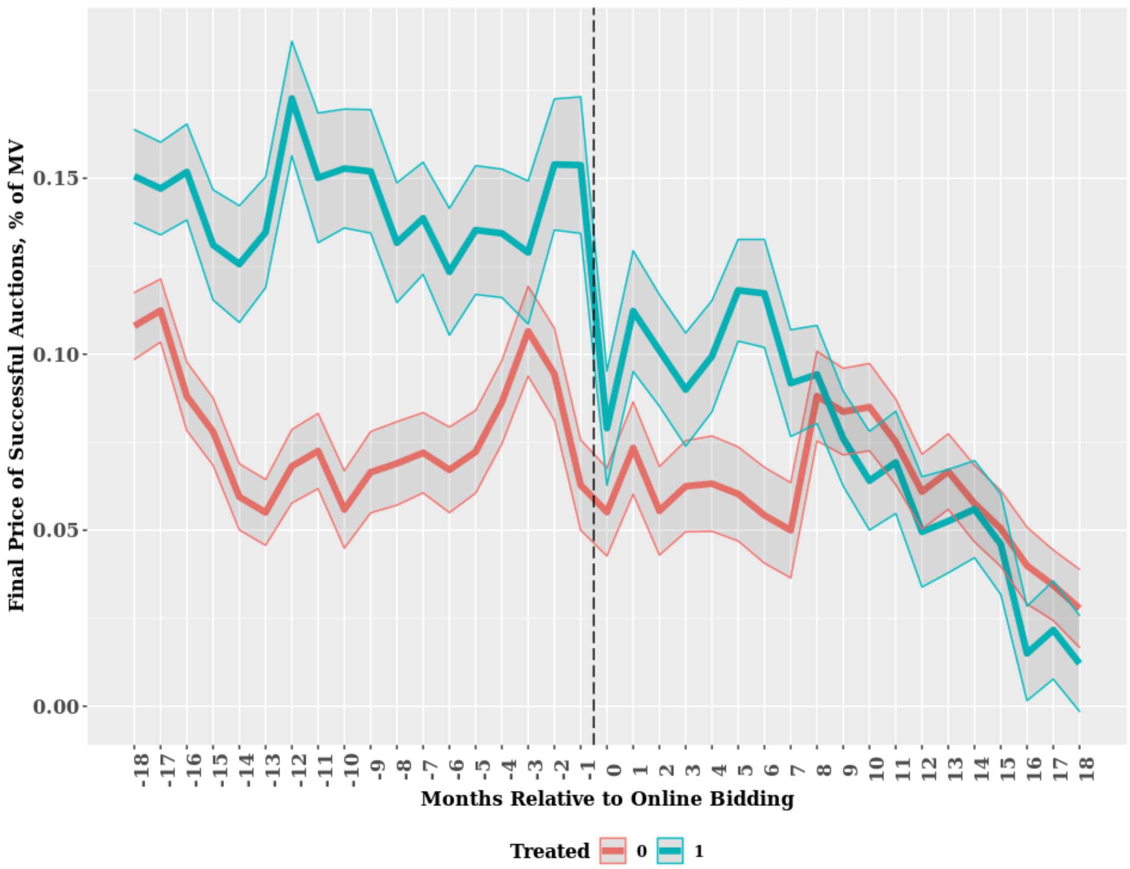


Figure 4: Auction discount, defined as 1 minus the ratio between the final price of a third-party foreclosure auction sale and the market value of the property assessed by county appraisers the year before. The values are averaged within treated (blue) counties and control (red) counties per month..

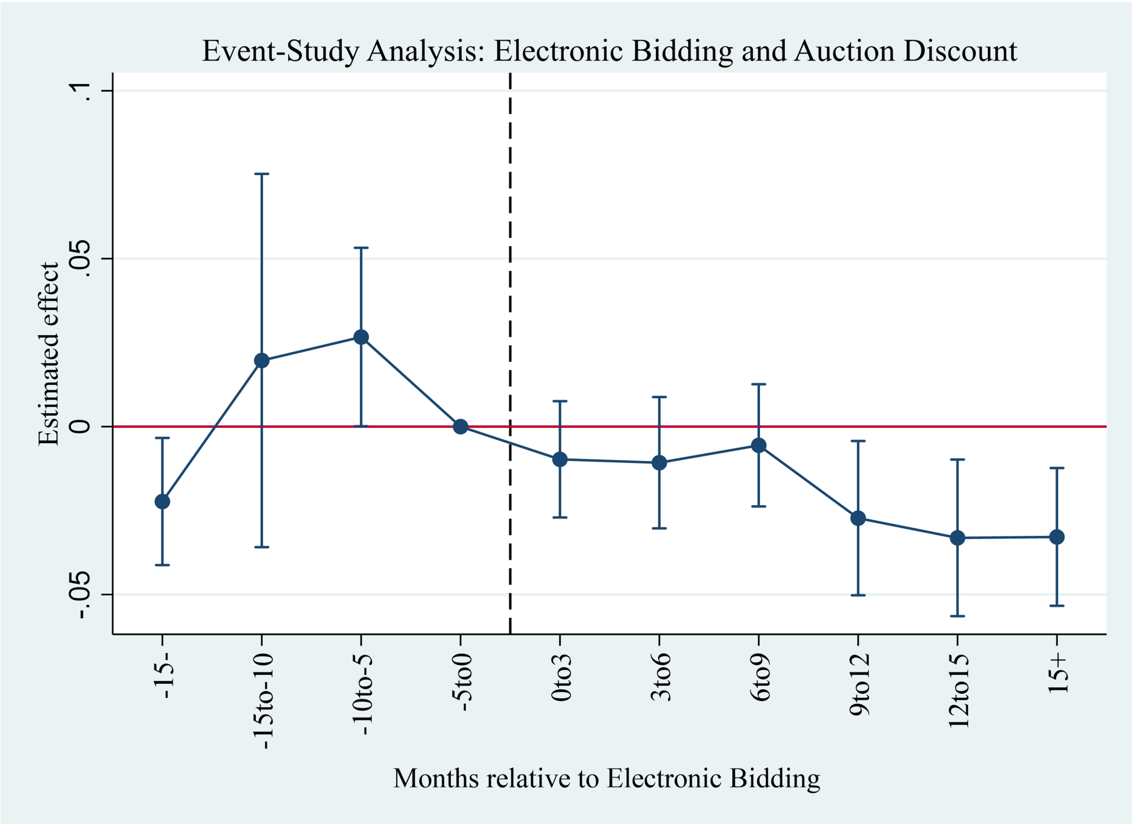
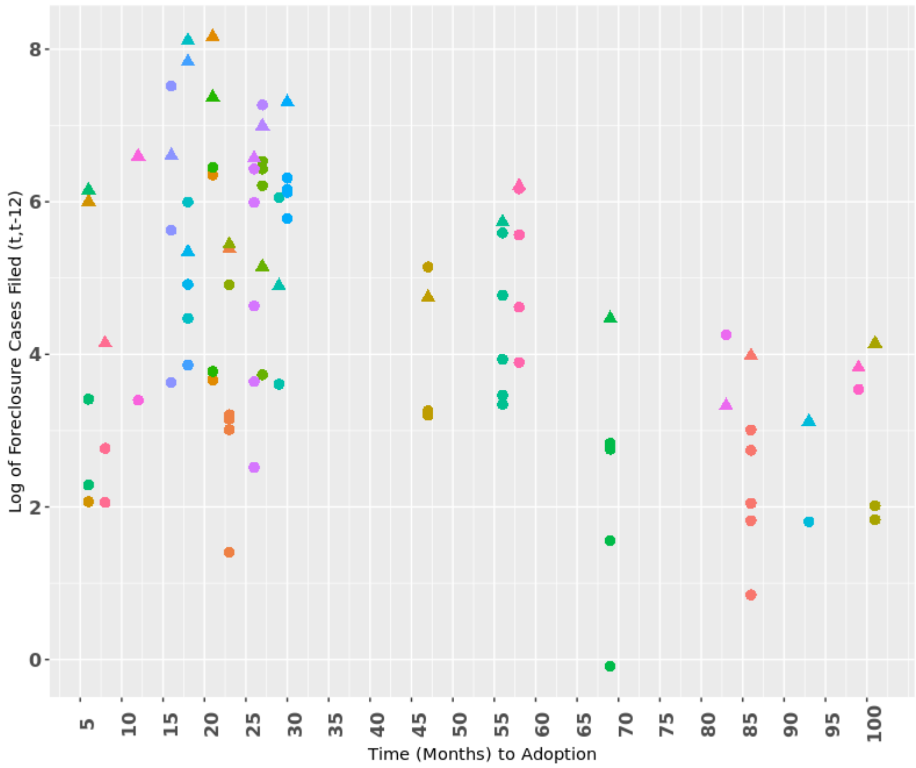
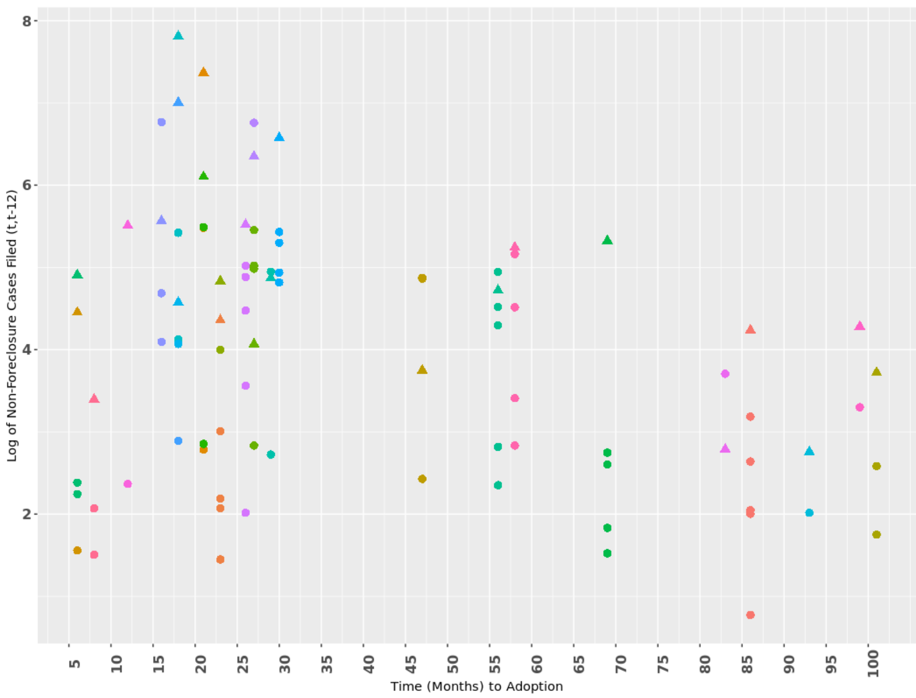


Figure 5: Event study estimates of electronic bidding on foreclosure auction discount. The point estimates are based on time indicators replacing the dummy $Post_t$ in model 1.



(a)



(b)

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.

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