Appendices

A Data Construction

A.1 Construction of Sample

A.1.1 Overview of Data Sources

This project uses data from several sources:

- Record Information Services (RIS): RIS is a company that aggregates many data sources for the Chicago area. We obtain several RIS datasets:
  - Court cases from 1998 to 2017: For each court case, this dataset contains the case number, the assessor's parcel number(s) (APN) of the property, defendant names, property address, time-varying property type (such as condo, apartment, single family home, etc), and some basic mortgage characteristics like loan amount.
  - Individual-level data: Crime, DUI convictions, bankruptcy, and divorces.
- Court cases from the Cook County Clerk of the Circuit Court (CC): We scrape information on each court case from 1998 to 2016 from the court's website. Information includes the case number, property address, plaintiff and defendant names, case filing date, and case calendar. Each case has a list of judgments, and each item in the list contains the judgment itself, the judge name, and the date.
- Infutor: Address histories for individuals who lived in Cook County, as well as name, age, gender, imputed race, and imputed immigration status.
- CoreLogic: Property tax and transaction records that indicate whether a person owns their primary residence.
- TransUnion (TU): Financial information including cumulative number of foreclosures, credit scores, number of open mortgages, and number of open loans with unpaid debt.
- IRS Statistics of Income Tax Stats: average annual income by ZIP code.
- Illinois Board of Education: Elementary, middle, and high school test scores.
- DataQuick: Tax assessor data on square footage of living space, transaction records indicating type of transaction including short sale and arms length sale.

A.1.2 Data Cleaning

1. Clean RIS: Drop all cases attached to multiple parcels because RIS may not report all of the APNs for these cases. More details:

   - First we de-duplicate cases by keeping the latest Input Date for each case, which constructs a dataset that is unique for each case number.
   - Then we drop all cases that map to multiple APNs.
   - Then we standardize RIS defendant addresses using the method described in Section A.7.
   - Some cases in RIS have missing APNs. We use case re-filings to recover 158 observations from the full 1998-2017 RIS dataset by replacing the missing APN with the APN of a different case with the same defendant name and address.
   - Some cases in RIS have APNs with typos. We replace 5,362 of these using the APN from DataQuick.

2. Clean Cook County court cases (CC): First we categorize cases into whether they are mortgage foreclosures, as detailed in Section A.3, and filter to only the mortgage foreclosure cases.

3. Merge RIS and CC using the court case number.

4. Constrain to the set of cases that have residential property types in RIS, which are single family, condo, townhome, and apartment building.

5. Drop cases for which we could not identify the foreclosure outcome. See Section A.4 for details.

6. Clean DataQuick Assessor data by dropping observations where multiple properties map to 1 APN or vice versa, which is only 2% of the data. This results in a dataset with unique APNs. Then we standardize the DQ site address as described in Section A.7.

7. Clean CoreLogic deeds and transaction records. We drop all properties that map to multiple APNs, which results in a dataset with unique APNs.

8. Clean Infutor migration histories. Section A.2 explains the steps in detail.

9. Find all people in Infutor who satisfy criteria for owner, landlord, and renter. These definitions are detailed in Section A.1.3.

A.1.3 Definitions of Owner, Renter, and Landlord

- Owner: The person in Infutor lives at the foreclosure address at the time of foreclosure filing and the last name matches. For condos, the apartment number of the address must also match. There are two criteria for matching the last name and the street address, noting that we standardize all addresses prior to matching to improve match rates:
  - The last name in Infutor matches exactly to the main defendant last name, and the case address string is entirely contained within the Infutor address string, OR
  - The street address in Infutor and for the case match exactly, and the last name of the defendant is a substring of the last name in Infutor, or the last name in Infutor is a substring of the last name of the main defendant, or the last name in Infutor is a substring of the list of all defendant first and last names (which helps capture cases where SMITH LLC matches to JOHN SMITH).

  If the addresses are similar but not identical in Infutor and the case filing, then the city and first name must also match. Another refinement is that if the last name doesn't match exactly, then we require the first name to be an exact match. If a property is owner-occupied, then no one living at the property can be a landlord.

- Renter: People who live in apartment buildings or condos, they were not a previous owner of the property (where previous owners are identified by examining the names of buyers and sellers in DQ transactions), and they are not the landlord.
  - They live at a property where we identify a landlord, OR
  - They live at a property that we are pretty sure is not owner-occupied. We know the property is not owner-occupied because we found multiple people in Infutor who may be the landlord because their first and last name match, but we can not be sure exactly which person is the actual landlord.

  We also require the state of the address to match, and either the city or ZIP code must match. For condos, the apartment number must match.

- Landlord: People who live at properties that are not owner-occupied and:
  - Live at the DataQuick mailing address at or before the foreclosure filing date, conditional on the DQ mailing addresses being different from the DQ site address. This procedure is similar to how owner names and addresses are matched, but instead of using the foreclosure filing address, we use the DataQuick mailing address. The only different is that landlords matched to condos don't need to have matching apartment numbers because they may live in any type of housing. This definition includes landlords who move away from the mailing address before the foreclosure filing date, OR
  - We can identify an implicit landlord. Here is how we search for implicit landlords:
    * First we identify everyone who has lived in Illinois at some point in their lives, and their first and last name matches the first and last name of the main defendant, and fewer than 10 people meet this criteria (to eliminate common names like John Smith).
    * If there is exactly 1 person who has the same name and has ever lived in Illinois, then we assign them to be the landlord.
    * Next, we require that entire address, street address, or ZIP code match. If there is exactly 1 person who has the same name and the address/street/ZIP matches, then we assign them to be the landlord. This is because landlords frequently live very close to their property.

A.2 Cleaning the Infutor Migration (IM) Data

The Infutor migration history contains address histories of individuals living in the U.S. from 1990 to 2016. Note that there are some addresses from before 1990, but they are more sparsely populated. We extract a data set of everyone who has ever lived in Cook County. Since the data set is large, we split it into small files based on where the current state where the individual lives, except for Illinois which has 5 files. In parentheses below are the approximate percentage of observed dropped at each step for two of the largest files, one for Illinois and one for California. Here are the cleaning steps:

- Construct begin and end dates for each address

  1. Infutor raw text data contains the following variables, all at the monthly level:

- date_orig: idate is the "original file date" according to Infutor documentation. This variable is unique at the person level.
    - We interpret this as the first date the person is observed by Infutor
- date_last: odate is the "last activity date" according to Infutor documentation. This variable is unique at the person level.
    - We interpret this as the last time the address history was verified.
- date_eff: Effective date is the "date of name/complete address combination" according to Infutor documentation. This variable is unique at the person-address level.
    - We choose effective date to define the start of each address. In most cases, effective date is same or similar to date_beg, conditional on date_beg existing. Effective date is far more well-populated than date_beg.
- date_beg: Begin date is the "original file date" according to Infutor documentation. This variable is unique at the person-address level.
    - It's hard to interpret what this variable actually means.
- date_end: End date is the "last verification date" according to Infutor documentation. This variable is unique at the person-address level.
    - For most people, date_end is only populated for the last address in the history. In most cases, date_end is same or similar to date_last, conditional on date_end existing.
- addnum: This is the address history sequence number, where 1 is the most recent address, and 10 is the earliest address. Not all people have 10 addresses, and no one has more than 10 addresses.

2. Drop addresses with missing effective dates (drops 5%): We drop all addresses that do not have an effective date because these addresses also typically do not have beginning and end date ranges, so very little information can be gleaned from these other than addnum, the address number. These addresses also tend to be the earliest address for a person.
3. To construct the date a person is first observed, called first_seen, we take the earliest date from date_eff, date_beg, date_end, date_orig, date_last.

4. To construct the date a person is last observed, last_seen, we take the latest date from date_eff, date_beg, date_end, date_orig, date_last.

5. Re-assign address numbers based on the revised effective date: Since we use effective date as the start of each address, the address numbers do not sequentially align with the sequence of effective dates, so we re-assign new addnum's based on effective date so that addnum reflects the address sequence accurately.

6. De-duplicate addresses by effective date (drops about 8%-12%): For a given person, some addresses have the same effective date, so we only need to keep the latest address.

   – Interpreted literally, it means that some people moved into a place and then moved out within the same month.

   – What this sometimes looks like in practice is that the same address is repeated twice, so it doesn't matter which address gets dropped.

7. Create address date range: Use effective date as the start date of each address. Use the effective date of next addnum as the end date of the address. For the final (most recent) address, the end date is imputed forward to be June 2017. We verify against Census data to determine that this method is the most sensible way to deal with the addresses that do not have a final end date. We construct a flag called bad_last_address (which affects 6%-10% of pid-address obs) to indicate that Infutor wasn't able to provide the end date for these addresses so the end date is imputed forward to be June 2017.

8. De-duplicate by address id (drop 4%-7%): If a person has 2 or more consecutive addresses with the same Infutor-defined address id, then we collapse them all into 1 address and adjust the beginning and end months accordingly to reflect the expanded date range.

- Standardize addresses: We standard street addresses and city names using the procedure described in Section A.7.

- Geocode addresses: We geocode every address in the Infutor address histories and link to 2010 Census block groups.

A.3 Identify cases that are mortgage foreclosures

For each case, we scrape the list of judgments issued from the Cook County Clerk of the Circuit Court website. For a given case, if the first judgment exactly matches any of the phrases below, then we categorize the case as a mortgage foreclosure. There are 458,412 such cases between 1997 and 2017 inclusive.

- mortgage foreclosure complaint filed
- owner occupied single family home or condominium - filed
- non owner occupied single family home or condominium - filed
- commercial, mixed commercial/residential or industrial - filed
- multi-unit residential mortgage foreclosure - (7 units or more) - filed
- owner occupied six units or less mortgage foreclosure - filed
- owner occupied, mixed commercial/residential - (6 units or less) - filed
- mortgage foreclosure disposed / sheriffs sale approved

A.4 Identify outcome for each case

We use court judgments to identify the outcome for each case and determine whether it results in foreclosure or dismissal. To identify foreclosures, we look for the judgment that says ”order for possession,” which means the owner must give up their house. To identify dismissals, we look for one of the following judgments:

- case dismissed subject to consent decree - allowed
- dismiss by stipulation or agreement
- dismiss entire cause
- dismissed for want of prosecution
- general chancery - voluntary dismissal, non suit, dismiss by agreement
- mechanic lien - voluntary dismissal, non-suit, dismiss by agreement

- mortgage foreclosure dismissed for want of prosecution
- mortgage foreclosure motion defendant dismissed
- mortgage foreclosure motion plaintiff dismissed
- mortgage foreclosure voluntary dismissal, non-suit or dismiss by agreement
- mortgage foreclosure judgment for defendant
- voluntary dismissal, non-suit or dismissed by agreement

In rare cases, judgments are overturned. This is evident for the cases with both judgments that indicate foreclosure and dismissal. For these types of cases, we take the most recent judgment. Furthermore, some cases were dismissed and then reinstated (reinstated cases contain the judgment "reinstate case - allowed -"), so we remove the dismissal categorization for those cases and rely on future judgments to classify the case. For our sample period from 2005 to 2012, this procedure enables us to categorize 97.8% of cases into foreclosure or dismissal. We drop the 6,104 cases that cannot be categorized using this algorithm.

A.5 Identify begin and end dates for each case

For each case, the online court record provides the Filing Date, which we take as the beginning date for each case. The court does not provide the end date, so we assign an end date for each case based on the date of the judgment used to determine the outcome of the case.

The main foreclosure outcome variable that we use is whether or not the case results in foreclosure 3 years after the filing date, including case refilings.

A.6 IRS Zip Code Income (IRS)

IRS contains annual income at the ZIP code level from 1998 to 2016. The data source is https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi. Here are the cleaning steps:

- Clean raw files: There are some messy Excel files which we clean. Then we aggregate these files across all years.
- Define income as:

- For each ZIP code, the files give the number of tax returns for each income bracket and the total Adjusted Gross Income (AGI) for that income bracket.
- Income for a ZIP code (call it ”AGI”) is the total AGI divided by total tax returns for each ZIP code in each year.
- We also calculate ”log AGI” by taking logs, and ”AGI percentile” by ranking the ZIP codes by income for each year.

- For a few observations, if there is a ZIP-year duplicate, we keep the observation with the larger value.
- There is no data available for 1999, 2000, 2003 so we interpolate values for those years.

A.7 Address Standardization

We frequently merge on addresses obtained from various sources like Infutor, RIS, and DataQuick. We develop the following method to standardize all addresses prior to merging to increase match rates:

- Construct standardized street address variables: the standardized full address (add_std), standardized address without the apartment/unit number (add_std_noaptnum), and the standardized apartment/unit number (add_std_unitval):

  1. First we use the Stata command stnd_address to extract the 1) street number and name, 2) PO Box, 3) building number, 4) floor number, and 5) unit number.
  2. Then we strip ”apt” and ”unit” strings and hyphens and other punctuation from the unit number so that only alphanumeric characters remain.
  3. Then we construct the standardized unit number variable add_std_unitval: the unit number is 3) building + 4) floor + 5) unit number. Most addresses only contain one of these fields. Only very rarely are 2 or more populated.
  4. Then we construct a version of the standardized address with no unit information, called add_std_noaptnum, which 1) street number and street name + 2) PO Box. This variable is useful because sometimes we do not want to require that the apartment number matches.
  5. Finally, we construct a standardized address with unit information, called add_std, which is obtained by combining add_std_noaptnum and add_std_unitval.

Table A.1: Variables from TransUnion (TU)

TU Variable in Paper	TU Variable Name
Credit Score (VantageScore 3.0)	CVTG03 - finscore
Death	TUPSCH1 - deadflag
Cumulative Number of Foreclosures	TUPSCH1 - foreclhh
Number of Unpaid Collections	TUPSCH1 - unpdcol
Number of Auto Loans	TUPSCH1 - auttrds
Number of Mortgages 30+ DPDs	TUPSCH1 - hmp2gn12
Number of Mortgages 90+ DPDs	TUPSCH1 - hmp4gn12
Number of Mortgages with Loan Mod	EADS142 - lm01s
Number of Open Mortgages	GMORTHE - mtn001
Open Mortgage Balance	GMORTHE - mtc004
Monthly Payment of All Mortgages	GMORTHE - mtp001

Notes: For TU Variable Names, the series of letters before the dash such as ”TUPSCH1” is the data group, which is how TU categorizes the variable. The series of letters after the dash such as ”foreclhh” is the variable name.

- Construct standardized city name, called add_city:

  1. We use abbreviations from the USPS and list of military suffixes to un-abbreviate any abbreviated city names: for example ”GDN” becomes ”GARDEN” and ”AFB” becomes ”AIR FORCE BASE”.

A.8 Variables from TransUnion (TU)

Table A.1 lists the variable names from TransUnion that correspond to each variable name referenced in the paper.

B Judge Instrumental Variable Appendix

B.1 Calendars and Judges

B.1.1 Overview

The Chancery Division of the Circuit Court of Cook County handles all mortgage foreclosure cases in Cook County. Since 2005, the court has randomly assigned cases to ”calendars” of cases. One can think of a calendar as a courtroom: There is a principal judge who typically handles cases along with backup judges in case the principal judge cannot handle the cases. In many cases, backup judges are shared across calendars. All mortgage foreclosure cases are heard at the same courthouse and there is a single randomization process for all cases in Cook County.

In particular, mortgage foreclosure cases are one of eight types of cases heard by the Chancery Division. Prior to 2005, mortgage foreclosure cases were heard by the General Chancery Section. However, due to rising case loads, in February of 2005, the Mortgage Foreclosure/Mechanics Lien (MF/ML) Section was created due to rising case loads. At this point we begin to have clear rules for randomization of mortgage foreclosure cases, which are randomly assigned separately from mechanics lien cases. In particular, ”one-fourth of all foreclosure cases were randomly assigned to the three mechanics lien judges, Calendars 52-54, and each of the three new judges, Calendars 55-57, received one-fourth of all foreclosure cases.”

Starting in May 2006, additional calendars were added due to high case volume. At that point, calendars 52, 53, and 54 received a third of 20 percent of the cases, while calendars 55, 56, 57, and 58 split the rest equally. Calendar 59 was added in July of 2007. On October 20, 2008, calendars 60-63 were added. Finally, on November 9, 2009, Calendar 64 was added and all remaining cases from calendars 52 through 54 were transferred to calendar 64.

In the data, we find evidence of significant calendar reassignment beyond calendar 64. In particular, it appears that as the court added calendars, they transferred existing cases to the new calendars. These cases were not randomly assigned, since they were existing cases that had taken longer to decide. This is an issue because in our scraped data, all we observe is the final calendar. Using this final calendar to create the instrument results in an instrument that is invalid because of non-random assignment.

While we only observe the final calendar of each case, we are still able to recover the initial calendar of all cases from our data. This is because we not only observe the final calendar of the case but also the date and judge on each judgement in the case. Based on the history of calendar creation from the court and the judges making judgements on cases decided before cases are reassigned across calendars, we create a record of the principal judge for each case. For cases that start before their final calendar is created, we determine the original calendar by observing the principal judge for the original calendar making judgements at the beginning of the case. Importantly, the original calendar assignment probabilities match the published probabilities from the court. We thus have random assignment of original calendars and can use the original calendar to create our instrument, which will be valid by random assignment.

The following two subsections detail our algorithm to reassign calendars and show that we replicate the court’s random assignment probabilities.

B.1.2 Reassigning Calendars to the Original Calendar

We first identify the main judge on each calendar in each month. To do so we use two definitions:

- A strict main judge makes at least 75% of the judgements on a calendar in a month based on final calendar AND at least 75% of the judge's judgements in a month are on that calendar.
- A weak main judge makes at least 75% of the judgements on a calendar in a month based on final calendar OR at least 75% of the judge's judgements in a month are on that calendar.

In finding the main judge, we limit ourselves to active calendars so that:

- Calendars 52, 53, and 54 finish having active judgements at the end of 2010 (even though they stop taking new cases between November 2008 and February 2009).
- Calendar 58 begins in May 2006
- Calendar 59 begins in July 2007
- Calendars 60-63 begin in October 2008
- Calendar 64 begins in November 2009

A potential issue with this method of identifying main judges is that a judge could switch calendars mid month and thus not show up as the main judge for either calendar in that month. We looked manually at the daily and weekly judgements and found this only happened in one cases, when Carolyn Quinn switches from calendar 54 to calendar 56 starting November 17, 2018. We manually adjust our main judges for this one case.

Once we have history of the principal judges for each calendar, we determine the original calendar for cases that are reassigned. Recall that cases are reassigned only to new calendars when they are introduced in order to spread the load more evenly. The concern is that reassignment is non-random because cases that take longer may have different foreclosure probabilities. We thus determine whether a case is reassigned based on it having a starting date (date of initial judgement) prior to the final calendar being created. In this case, we know that the case had to have been reassigned to that calendar.

In particular, we count the number of judgements on each case that are made by the main judge on each calendar and do not count calendars that are reassignments based on the day the case started relative to the date the calendar was created. If one calendar has the most judgements by a main judge of a potential original calendar, we set that calendar as the original calendar. We do this initially for the strict definition of a main judge. 96.01% of the cases have an original calendar assigned this way. The remaining 3.99% either have no judgements by a strict main judge of a potential original calendar or have a tie between two potential original calendars.

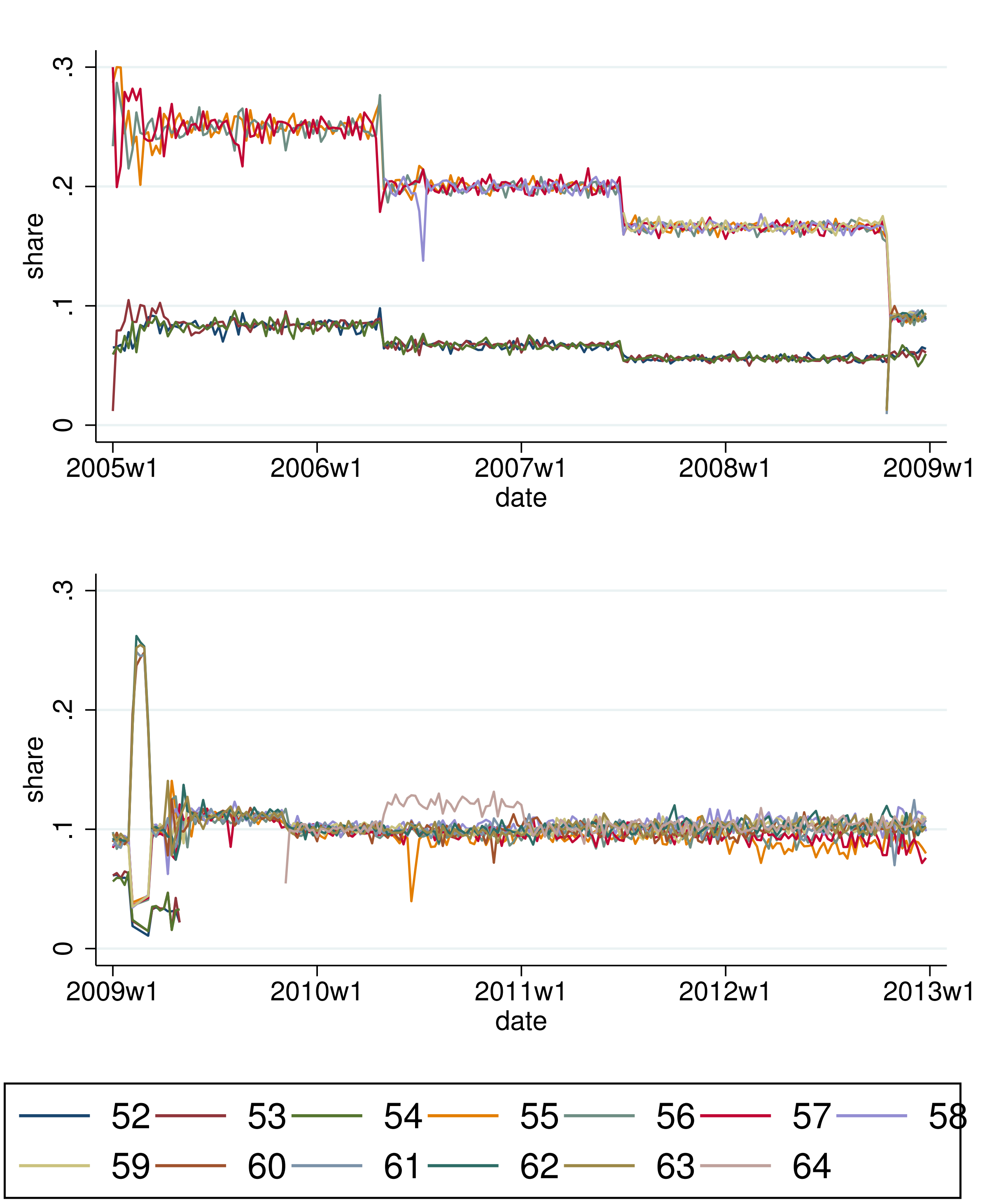
For these 3.99% of cases, we repeat the process using progressively weaker definitions of the main judge. First, we use the weak main judge definition above. This gets 3.33% of the 3.99% of cases that need to be reassigned. We then do three additional methods for the last 0.66% of cases. First, we include judges who are not the only main judge on a calendar. Then we go back to the strict main judge definition and break ties based on which of the tied main judges ruled first. We then repeat this tie-breaking procedure using the weak main judge definition. In the end, essentially all cases are assigned to an original calendar using this method.

B.1.3 Relationship Between Our Assignment Probabilities and Published Assignment Probabilities

Figure A.1 shows the share of cases assigned to each calendar by week over our sample using the original calendar variable. We can see that the assignment probabilities are generally very stable, have discrete jumps corresponding to the dates when new calendars are introduced according to court records, and correspond to the published assignment probabilities in periods where assignment probabilities are public.

In particular, the court documentation indicates that from the beginning of 2005 until may 2006, calendars 52, 53, and 54 split a quarter of the cases three ways while calendars 55, 56, and 57 each took 25 percent, which is exactly what we observe. Then in May 2006, calendar 58 is added and calendars 52, 53, and 54 split 20% of the cases three ways while calendars 55, 56, 57, and 58 each get 20 percent. In July of 2007, Calendar 59 is added. Although we were unable to find published probabilities for this addition or subsequent additions, it seems that they followed the same rule: we can see that calendars 52, 53, and 54 split one sixth of the cases and each of the other calendars gets one sixth of the cases. In October of 2008, court documents indicate that four additional calendars were added. We observe the randomization probabilities change at this time. However, rather than reducing the load for calendars 52, 53, and 54, it appears that the cases divided between the remaining calendars decline and then in early 2009 these four calendars randomization probabilities rise as their case load is filled up while calendars 52-54 are phased out. Unfortunately, we could not find court documentation of this process. Finally, in November

Figure A.1: Share of Cases Assigned to Each Calendar By Week



Notes: The figure shows the share of cases assigned to each calendar in each week from 2005 to 2012.

2009 Calendar 64 is added and the randomization probabilities for the remaining calendars is 10% for the rest of the sample aside for a period in 2010 when Calendar 64 has a higher probability, presumably to increase its caseload.

The fact that we have stable assignment probabilities (with some noise) that replicate published probabilities when available indicates to us that our case reassignment algorithm does a good job identifying the original randomly-assigned calendar. In the main body we also show several placebo tests to confirm random assignment conditional on the date a case starts.

B.2 Monotonicity

To obtain a valid LATE, IV requires a monotonicity assumption that an increase in the judge's average foreclosure probability must increase the foreclosure probability for all foreclosure cases. In other words, a strict judge must be strict for everyone, and a lenient judge must be lenient for everyone. One concern that this may not hold for judge assignment if, for instance, some judges were strict for types of defendants but not others. A commonly cited example of this is a case where judges are lenient to defendants of their own race and strict for defendants of other races.

Table A.3 addresses these concerns by estimating the first stage equation (3) for different judge characteristics (gender and race) and defendant characteristics (gender, race, age, immigrant status, presence of an attorney, ZIP-Income Quintile, and Mortgage Size Quartile). We do not find any statistically-significant negative coefficients, and with a few exceptions where we have very little data and the standard errors widen, we have significant and positive coefficients. We conclude that we find no significant evidence of a violation of monotonicity.

C Propensity Score Matching Appendix

C.1 Propensity Score Construction Details

Section 3.3 describes how we construct propensity scores using equation (5). In this section, we detail how we select the lagged observables $X_{i,s-3}$ that we use to create the propensity scores. In particular, we run equation (5) with 21 different $X_{i,s-3}$ for owners, renters, and landlords. The outcomes include 11 non-credit outcomes (Moved from foreclosure address; owns primary residence; log living square footage; average log ZIP-income; elementary school test score rank; middle school test score rank; high school test score rank; cumulative number of divorces; cumulative number of crimes convicted; cumulative number of bankruptcies; and cumulative number of DUI

Table A.2: Propensity Score Prediction using Observables at Year -3

Dependent Variable:	1 if Foreclosed within 3 Years After Filing		
Subgroup:	Owner	Landlord	Renter
	(1)	(2)	(3)
Owns Primary Residence at pre3	-0.0820***		
	(0.0015)		
Living Square Footage at pre3	-0.0174***	-0.0088***	-0.0122**
	(0.0015)	(0.0033)	(0.0055)
Credit Scores at pre3	0.0046***		
	(0.0013)		
Number of Mortgages 30+ DPDs at pre3	-0.0232***	-0.0356***	-0.0042*
	(0.0013)	(0.0029)	(0.0023)
Number of Open Mortgages at pre3	0.0064***		
	(0.0013)		
Moved from Foreclosure Address at pre3		0.0113***	
		(0.0025)	
Number of Foreclosures at pre3		0.0131***	0.0044*
		(0.0030)	(0.0024)
Monthly Mortgage Payment at pre3		-0.0050*	
		(0.0026)	
Cumulative Number of Crimes Convicted at pre3			0.0039*
			(0.0021)
Number of Unpaid Collections at pre3			0.0045*
			(0.0023)
Constant	0.3383***	0.5362***	0.5742***
	(0.0013)	(0.0022)	(0.0040)
R^2	0.076	0.147	0.371
Observations	248,494	60,051	80,132

Notes: This table reports estimation results for equation (5) that we use to predict propensity scores for owners, landlords, and renters. Observations are at the case-person level. The dependent variable is the foreclosure variable, which takes value 1 if the property associated with the case was foreclosed within three years after filing; and 0 otherwise. For each subgroup, we choose the 5 covariates from 21 covariates at year -3 that are most highly correlated with our foreclosure variable. We assign a group average whenever the value is missing and also normalize all covariates to have mean 0 and standard deviation 1 within each subgroup. All regressions absorb date of filing and zip-year fixed effects. We use the inverse of the number of people per case as weight for owners and landlords, but do not weight renters. Robust standard errors are clustered by case. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

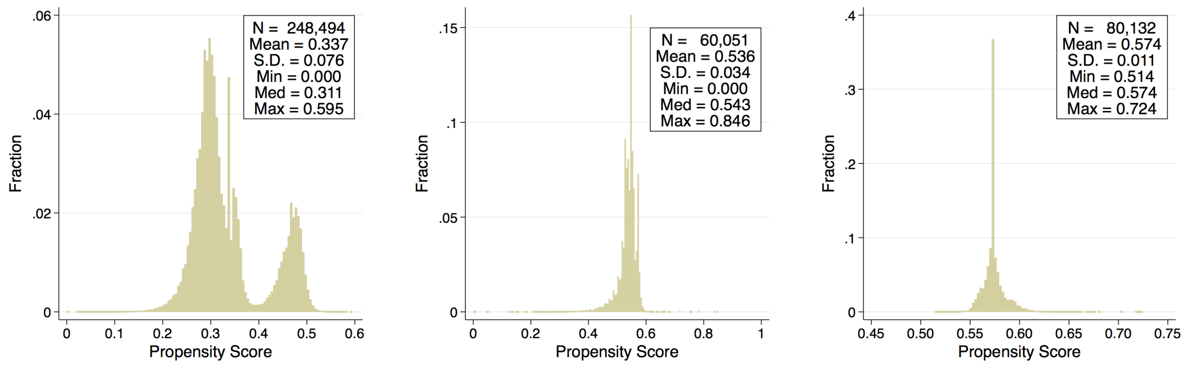
Table A.3: Monotonicity Tests: First Stage Regressions by Defendants' and Judge's Characteristics

	Any Judge	**By Main Judge's Characteristic**			
		Male	**Female**	**White**	**Non-white**
Any Defendant	0.692***	0.710***	0.449***	0.684***	0.530***
	(0.056)	(0.072)	(0.144)	(0.075)	(0.130)
By Gender					
- both male and female	0.672***	0.746***	0.648**	0.808***	0.650**
	(0.109)	(0.142)	(0.306)	(0.148)	(0.267)
- male only	0.726***	0.661***	0.697**	0.675***	0.580**
	(0.101)	(0.131)	(0.280)	(0.137)	(0.235)
- female only	0.542***	0.635***	-0.042	0.442***	0.260
	(0.107)	(0.138)	(0.342)	(0.148)	(0.266)
By Race					
- white only	0.674***	0.726***	0.418	0.673***	0.669***
	(0.099)	(0.129)	(0.276)	(0.137)	(0.226)
- non-white	0.690***	0.698***	0.426**	0.678***	0.449***
	(0.069)	(0.089)	(0.178)	(0.091)	(0.164)

By Age					
- old	0.626***	0.735***	0.160	0.544***	0.668***
	(0.092)	(0.117)	(0.241)	(0.122)	(0.215)
- young	0.736***	0.760***	0.370	0.821***	0.373*
	(0.084)	(0.112)	(0.229)	(0.116)	(0.205)
By Immigrant Status					
- both immigrants and locals	0.639**	0.401	0.599	0.218	0.518
	(0.287)	(0.412)	(0.917)	(0.408)	(1.023)
- immigrants only	0.899***	0.971***	-0.264	0.967***	1.109**
	(0.190)	(0.250)	(0.627)	(0.267)	(0.507)
- locals only	0.581***	0.644***	0.227	0.699***	0.301
	(0.079)	(0.106)	(0.208)	(0.110)	(0.192)
By Presence of Attorney					
- no attorney	0.684***	0.706***	0.442***	0.689***	0.504***
	(0.057)	(0.074)	(0.149)	(0.077)	(0.133)
- has attorney	1.362***	1.421***	-0.267	1.285***	1.823
	(0.337)	(0.487)	(1.253)	(0.482)	(1.296)
By Zip-Income Quintile					
- 1st quintile	0.531***	0.605***	0.383	0.516***	0.443
	(0.126)	(0.171)	(0.319)	(0.173)	(0.307)
- 2nd quintile	0.705***	0.619***	0.267	0.726***	0.073
	(0.129)	(0.169)	(0.385)	(0.171)	(0.343)
- 3rd quintile	0.795***	0.843***	0.466	0.858***	0.856***
	(0.139)	(0.180)	(0.438)	(0.198)	(0.326)
- 4th quintile	0.913***	0.718***	1.260***	0.820***	0.532*
	(0.134)	(0.171)	(0.401)	(0.183)	(0.317)
- 5th quintile	0.620***	0.792***	0.242	0.743***	0.377
	(0.132)	(0.168)	(0.388)	(0.179)	(0.314)
By Mortgage Size Quartile					
- 1st quartile	0.543***	0.543***	-0.341	0.473***	0.341
	(0.110)	(0.162)	(0.345)	(0.168)	(0.303)
- 2nd quartile	0.577***	0.687***	0.444	0.566***	0.511*
	(0.111)	(0.137)	(0.337)	(0.148)	(0.265)
- 3rd quartile	0.900***	0.884***	0.689**	1.017***	0.662**
	(0.121)	(0.153)	(0.308)	(0.157)	(0.282)
- 4th quartile	0.763***	0.731***	0.748**	0.783***	0.683**
	(0.121)	(0.154)	(0.296)	(0.160)	(0.273)

Note: Each entry in the table shows first stage regression coefficients following equation (3) for the indicated defendant and judge characteristics. All standard errors are clustered by case, and we weight by the inverse of the number of people per case for owners and landlords so that each foreclosure case is weighted equally. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure A.2: Propensity Score Distribution



(a) Owners (b) Landlords (c) Renters

Notes: This figure displays the distributions of our propensity scores for owners, landlords, and renters. We also report summary statistics in the figure.

convictions) and 9 outcomes from credit reports (Credit score; number of foreclosures from past 12 months; number of unpaid collections; number of auto trades; number of mortgages with 30+ days past due from past 12 months; number of mortgages with loan modification; number of open mortgages; total mortgage balance as a fraction of RIS complaint amount; and annual mortgage payment as a fraction of RIS amount). We normalize each outcome to have mean 0 and standard deviation 1 within each subgroup and assign the subgroup average if an outcome is missing. We then choose the 5 covariates with the largest magnitude and highest statistical significance and include these five covariates as the final $X_{i,s-3}$ we use when we estimate equation (5) to construct the propensity score.

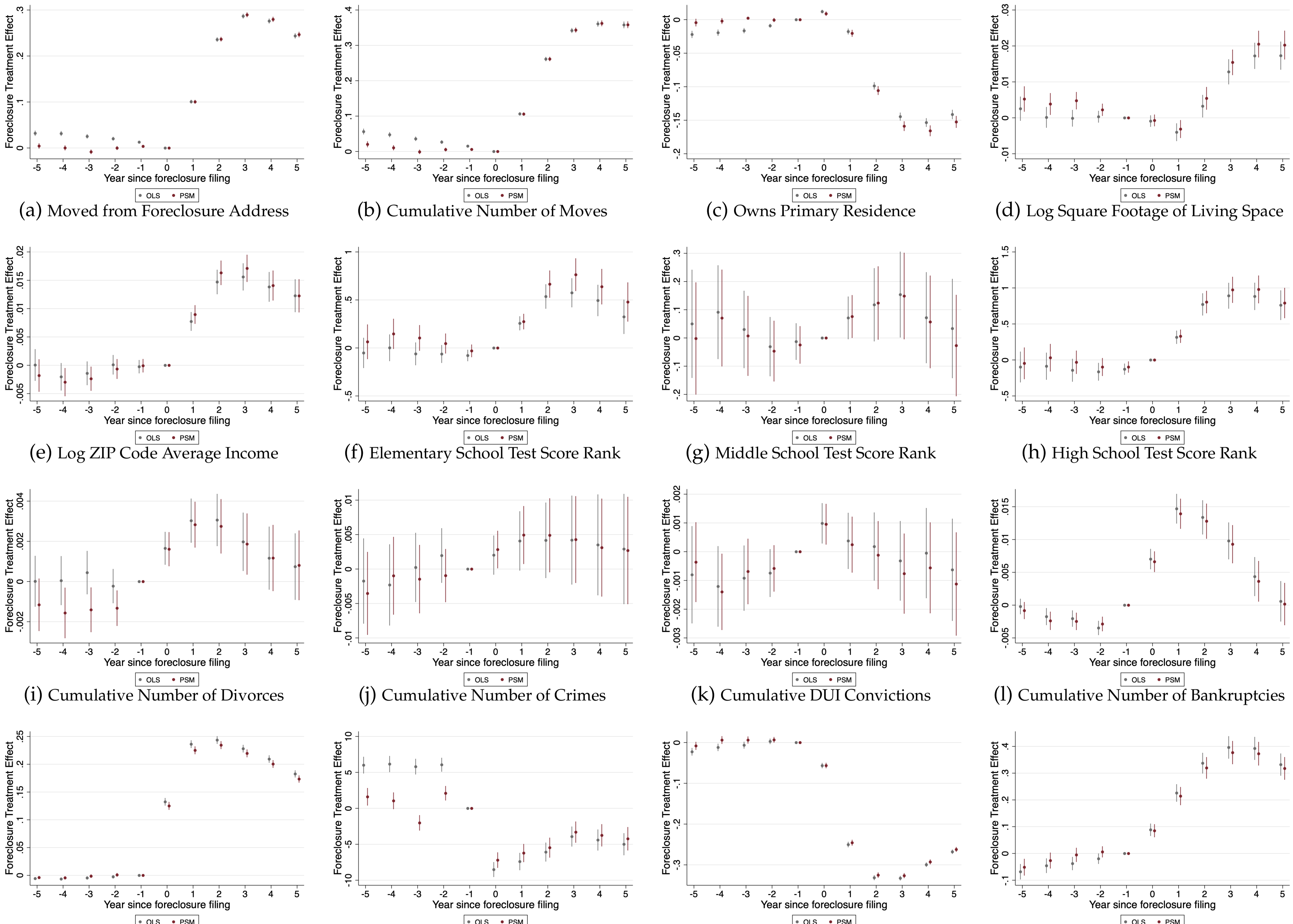
Tables A.2 shows the final regressions we use to create the propensity score for owners, renters, and landlords along with the five observables we use for each subgroup. The propensity score is $\hat{\alpha}X_{i,s-3}$ from this regression. We present the distributions and summary statistics of propensity scores in Figure A.2.

C.2 OLS vs. PSM

In the main text, we use PSM rather than OLS for everything but our heterogeneity analyses. In Figures A.3, A.4, and A.5, we present all of our main results for both OLS and PSM so the reader can compare the two. We use the exact same specification as in the main text for PSM, except the fixed effects in OLS do not condition on the propensity score deciles.

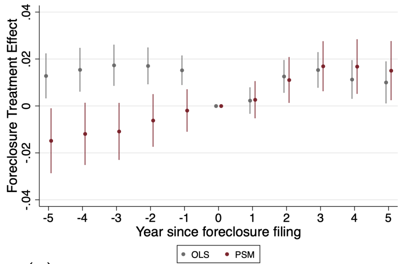
As mentioned in the main text, PSM helps remove pre-trends that are present in OLS for many outcomes. This can be seen, for instance, for moving, the cumulative number of moves, and

Figure A.3: OLS vs. PSM — Owners

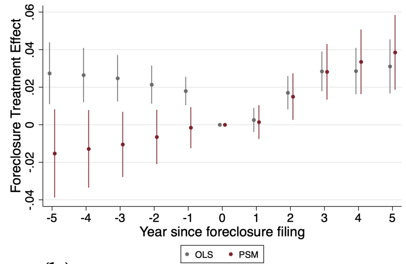


(a) Moved from Foreclosure Address
(b) Cumulative Number of Moves
(c) Owns Primary Residence
(d) Log Square Footage of Living Space
(e) Log ZIP Code Average Income
(f) Elementary School Test Score Rank
(g) Middle School Test Score Rank
(h) High School Test Score Rank
(i) Cumulative Number of Divorces
(j) Cumulative Number of Crimes
(k) Cumulative DUI Convictions
(l) Cumulative Number of Bankruptcies
(m) Cumulative Number of Foreclosures
(n) Credit Score
(o) Number of Open Mortgages
(p) Number of Unpaid Collections

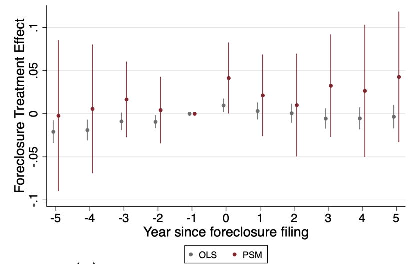
Figure A.4: OLS vs. PSM — Landlords



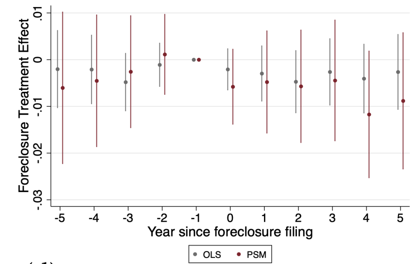
(a) Moved from Foreclosure Address



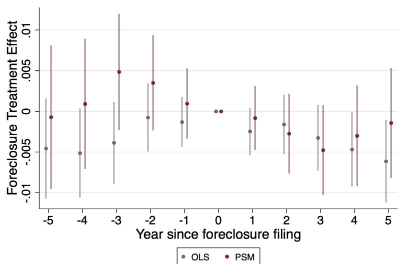
(b) Cumulative Number of Moves



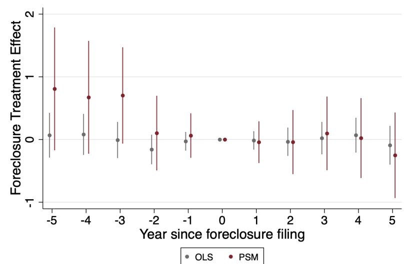
(c) Owns Primary Residence



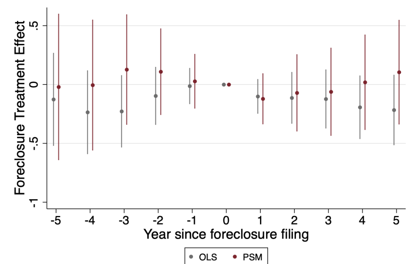
(d) Log Square Footage of Living Space



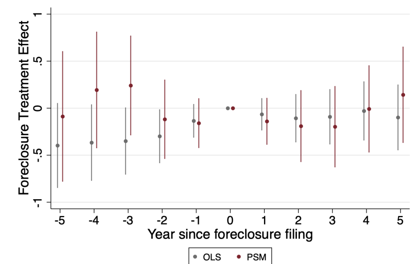
(e) Log ZIP Code Average Income



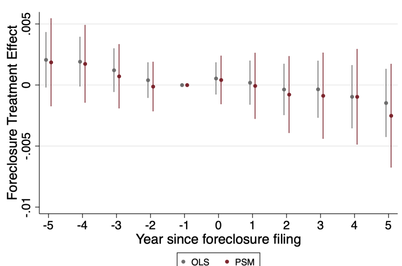
(f) Elementary School Test Score Rank



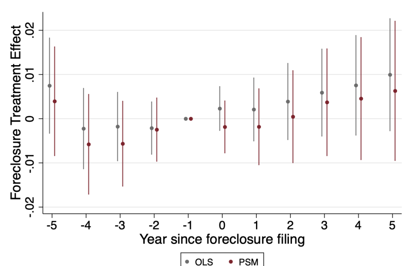
(g) Middle School Test Score Rank



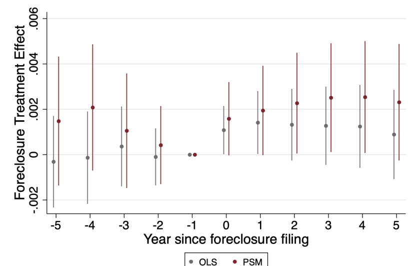
(h) High School Test Score Rank



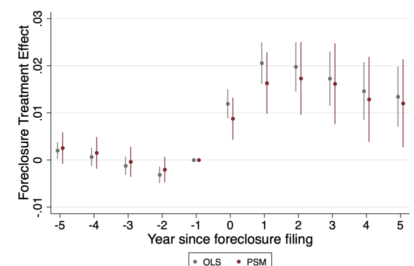
(i) Cumulative Number of Divorces



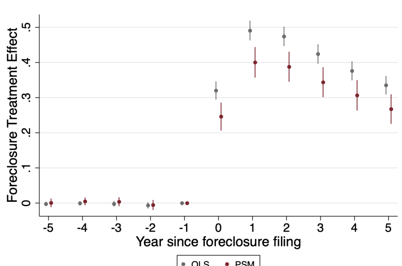
(j) Cumulative Number of Crimes



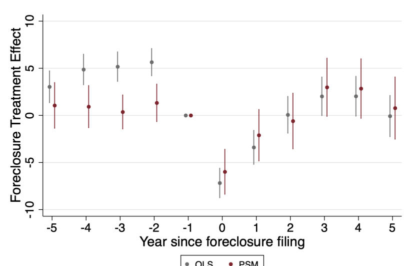
(k) Cumulative DUI Convictions



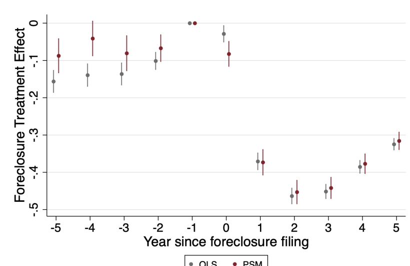
(l) Cumulative Number of Bankruptcies



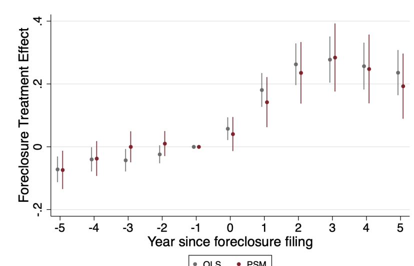
(m) Cumulative Number of Foreclosures



(n) Credit Score

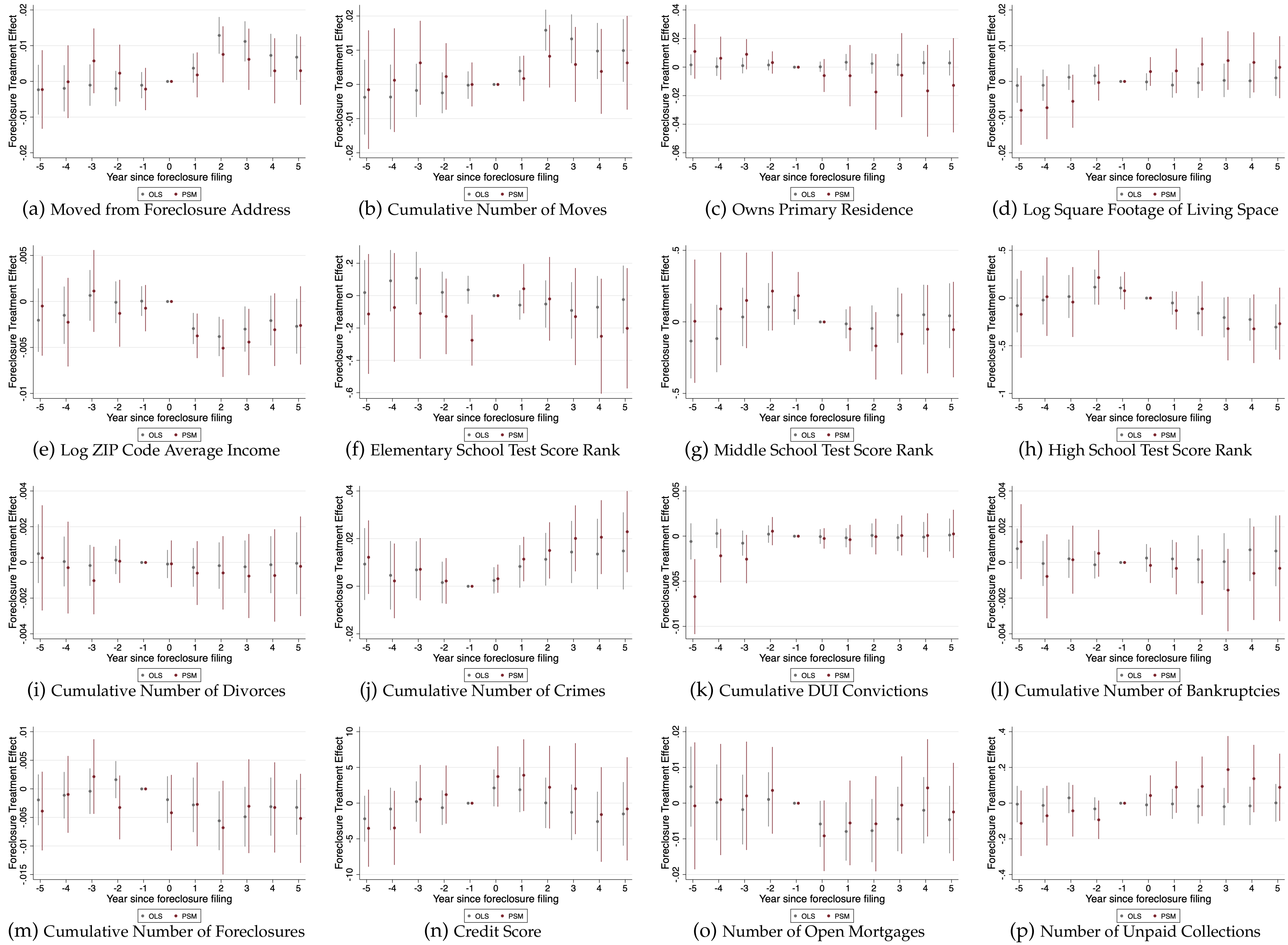


(o) Number of Open Mortgages



(p) Number of Unpaid Collections

Figure A.5: OLS vs. PSM — Renters



(a) Moved from Foreclosure Address
(b) Cumulative Number of Moves
(c) Owns Primary Residence
(d) Log Square Footage of Living Space
(e) Log ZIP Code Average Income
(f) Elementary School Test Score Rank
(g) Middle School Test Score Rank
(h) High School Test Score Rank
(i) Cumulative Number of Divorces
(j) Cumulative Number of Crimes
(k) Cumulative DUI Convictions
(l) Cumulative Number of Bankruptcies
(m) Cumulative Number of Foreclosures
(n) Credit Score
(o) Number of Open Mortgages
(p) Number of Unpaid Collections

owning a primary residence for owners. These pre-trends tend to be stronger for renters and landlords since samples are smaller. PSM generally improves pre-trends, which is why we prefer it. However, it is worth noting that most of our main results for PSM are present in OLS as well; PSM improves their measurement but does not create the result from whole cloth. There are a few notable exceptions, such as the number of unpaid collections for renters. As mentioned in the main text, this is one of the few cases where PSM shows a significant result that is not present in OLS and where OLS has clean pre-trends. We discount the PSM results that are not also present in OLS.

D Additional Results

D.1 Additional OLS Heterogeneity Results

In Section 4.5 of the main text, we present an analysis of heterogeneity in OLS to show that our full-sample IV results are consistent with OLS for various sub-samples. We argue this is consistent with treatment effect heterogeneity, with PSM/OLS picking up an average treatment effect and IV picking up a LATE for compliers to the judge instrument. In this section, we present some additional heterogeneity results in OLS to show that IV is consistent with OLS for various sub-samples for results that were not shown in Section 4.5.

Figure A.6 shows IV results for the full samples together with OLS for two restricted samples: black renters with any landlord in panel A and black renters with white landlords in panel B. Panel A shows that black renters with any landlord closely matches the full sample OLS results in Figure 14a. However, the black renters with white landlord subsample closely matches OLS. In Section 6 we argue that because the lender takes over the property in the case of a foreclosure and landlord characteristics should cease to matter at that point, the fact that the foreclosed-upon landlord's race matters is indicative of white landlords with minority tenants being likely to evict if they avoid foreclosure in marginal cases.

Finally, Figure A.7 shows that heterogeneity can also explain the gap between IV and PMS for landlord DUI convictions. We find a group of younger landlords who have OLS results that look like our full sample IV, indicating that treatment effect heterogeneity for marginal relative to average landlords can explain the DUI results.

Table A.4: Treatment Effect Summary using Alternative Definitions of Foreclosure, Owner

Foreclosure Definition:	Court Decision		Corelogic Deeds		Moved or Not	
Specification:	IV	PSM	IV	PSM	IV	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Moved from Foreclosure Address	0.289***	0.285***	0.341***	0.290***	0.414***	0.368***
	(0.081)	(0.003)	(0.102)	(0.003)	(0.103)	(0.002)
Cumulative Number of Moves	0.390***	0.352***	0.464***	0.363***	0.552***	0.466***
	(0.110)	(0.004)	(0.140)	(0.004)	(0.143)	(0.003)
Owns Primary Residence	-0.220**	-0.166***	-0.178	-0.184***	-0.356***	-0.327***
	(0.106)	(0.004)	(0.134)	(0.004)	(0.135)	(0.004)
Log Square Footage of Living Space	-0.021	0.022***	-0.051	0.028***	-0.018	0.025***
	(0.051)	(0.002)	(0.061)	(0.002)	(0.062)	(0.002)
Log Zip Code Average Income	-0.106**	0.016***	-0.141***	0.017***	-0.129**	0.023***
	(0.041)	(0.001)	(0.053)	(0.001)	(0.058)	(0.001)
Elementary School Test Score Rank	-3.282	0.711***	-4.894	0.706***	-7.162*	0.758***
	(2.769)	(0.097)	(3.414)	(0.100)	(3.841)	(0.086)
Middle School Test Score Rank	-6.143**	0.101	-9.926***	0.222**	-5.913	0.176**
	(2.851)	(0.088)	(3.558)	(0.091)	(3.712)	(0.076)
High School Test Score Rank	-3.025	0.988***	-5.297	1.032***	-3.126	1.235***
	(3.107)	(0.101)	(3.913)	(0.104)	(4.168)	(0.088)
Cumulative Number of Divorces	0.065**	0.002*	0.077**	0.001	0.113***	0.002***
	(0.028)	(0.001)	(0.033)	(0.001)	(0.042)	(0.001)
Cumulative Number of Crimes Convicted	0.023	0.005	0.004	0.001	-0.075	0.001
	(0.100)	(0.004)	(0.122)	(0.004)	(0.151)	(0.003)
Cumulative Number of Bankruptcies	0.027	0.006***	0.031	0.001	-0.056	-0.006***
	(0.048)	(0.002)	(0.057)	(0.001)	(0.069)	(0.001)
Cumulative Number of DUI Convictions	0.017	-0.001	0.016	-0.001	0.007	-0.001*
	(0.022)	(0.001)	(0.025)	(0.001)	(0.033)	(0.001)
VantageScore	-13.866	-3.538***	-25.941	-1.383*	-3.595	0.563
	(25.752)	(0.733)	(33.279)	(0.742)	(34.125)	(0.662)
Death	0.006	0.008***	0.020	0.007***	0.007	0.009***
	(0.026)	(0.001)	(0.031)	(0.001)	(0.036)	(0.001)
Number of Foreclosures	0.085	0.210***	0.099	0.205***	-0.039	0.187***
	(0.097)	(0.003)	(0.117)	(0.003)	(0.140)	(0.003)
Number of Unpaid Collections	1.250*	0.375***	1.490*	0.356***	1.069	0.297***
	(0.666)	(0.021)	(0.836)	(0.022)	(0.921)	(0.019)
Number of Auto Loans	-0.152	-0.022***	-0.308	-0.004	-0.154	0.013**
	(0.210)	(0.006)	(0.260)	(0.007)	(0.287)	(0.006)
Number of Mortgages 90+ DPDs	-0.288	-0.248***	-0.327	-0.263***	-0.420	-0.307***
	(0.246)	(0.007)	(0.306)	(0.007)	(0.327)	(0.007)
Number of Mortgages with Loan Mod	0.036	-0.099***	0.060	-0.092***	0.028	-0.122***
	(0.053)	(0.001)	(0.065)	(0.001)	(0.073)	(0.001)
Number of Open Mortgages	-0.260***	-0.310***	-0.336***	-0.298***	-0.260**	-0.374***
	(0.095)	(0.003)	(0.120)	(0.003)	(0.127)	(0.003)
Open Mortgage Balance / RIS Amount	-0.416***	-0.307***	-0.468**	-0.311***	-0.439**	-0.396***
	(0.157)	(0.006)	(0.194)	(0.006)	(0.213)	(0.006)

Notes: This table shows PSM and IV results for owners for years 3 and 4 relative to the base year as in Table 7 for three different foreclosure definitions. The first two columns labeled ”Court Decision” uses the foreclosure definition of a foreclosure occurring within three years of filing according to the court records. The second two columns labeled ”Corelogic Deeds” uses a definition based on whether we observe a foreclosure in the CoreLogic deeds data within three years of the initial court filing rather than using court records of a foreclosure occurring. The third two columns labeled ”Moved or Not” uses a definition based on whether we observe a sale (foreclosure or non-foreclosure) in the deeds data within three years of the initial court filing. For all three definitions, we re-create the judge leniency instrument using the new foreclosure definition. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.5: Treatment Effect Summary using Alternative Definitions of Foreclosure, Landlord

Foreclosure Definition:	Court Decision		Corelogic Deeds		Moved or Not	
Specification:	IV	PSM	IV	PSM	IV	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Moved from Foreclosure Address	0.050	0.017***	0.072	0.020***	-0.033	0.041***
	(0.161)	(0.006)	(0.202)	(0.006)	(0.321)	(0.006)
Cumulative Number of Moves	-0.042	0.031***	-0.103	0.036***	-0.209	0.076***
	(0.235)	(0.008)	(0.309)	(0.008)	(0.479)	(0.009)
Owns Primary Residence	0.339*	0.027	0.778	0.002	0.595	0.024
	(0.204)	(0.036)	(0.483)	(0.037)	(0.442)	(0.042)
Log Square Footage of Living Space	-0.106	-0.009	-0.088	-0.004	-0.261	-0.011
	(0.117)	(0.007)	(0.128)	(0.007)	(0.253)	(0.007)
Log Zip Code Average Income	0.127	-0.004	0.206*	-0.008***	0.426*	0.004
	(0.088)	(0.003)	(0.112)	(0.003)	(0.231)	(0.003)
Elementary School Test Score Rank	0.324	0.045	2.583	-0.182	9.517	0.109
	(6.803)	(0.310)	(7.960)	(0.305)	(11.657)	(0.333)
Middle School Test Score Rank	-6.317	0.001	-0.054	-0.033	-15.331	0.225
	(5.583)	(0.197)	(6.364)	(0.194)	(10.717)	(0.206)
High School Test Score Rank	-6.568	-0.085	-0.032	-0.173	-11.104	0.425*
	(5.884)	(0.226)	(7.333)	(0.225)	(11.199)	(0.237)
Cumulative Number of Divorces	-0.065	-0.001	-0.085	-0.000	-0.105	-0.000
	(0.051)	(0.002)	(0.058)	(0.002)	(0.095)	(0.002)
Cumulative Number of Crimes Convicted	0.157	0.008	0.112	0.012	0.014	0.008
	(0.181)	(0.009)	(0.196)	(0.009)	(0.381)	(0.009)
Cumulative Number of Bankruptcies	0.095	0.015***	0.046	0.010**	0.141	-0.006
	(0.127)	(0.004)	(0.165)	(0.004)	(0.242)	(0.005)
Cumulative Number of DUI Convictions	0.058*	0.003**	0.063	0.003**	0.077	0.000
	(0.033)	(0.001)	(0.040)	(0.001)	(0.062)	(0.001)
VantageScore	10.422	2.909*	20.543	5.079***	48.575	14.447***
	(36.319)	(1.526)	(42.339)	(1.530)	(79.688)	(1.652)
Death	0.022	0.002	-0.005	0.001	-0.034	-0.000
	(0.039)	(0.002)	(0.046)	(0.002)	(0.084)	(0.002)
Number of Foreclosures	0.055	0.325***	0.444	0.288***	0.016	0.254***
	(0.492)	(0.021)	(0.509)	(0.021)	(1.074)	(0.024)
Number of Unpaid Collections	0.379	0.264***	-0.086	0.213***	-1.645	0.054
	(1.198)	(0.053)	(1.359)	(0.053)	(2.585)	(0.058)
Number of Auto Loans	-0.324	0.016	-0.422	0.015	-0.002	0.033*
	(0.409)	(0.017)	(0.476)	(0.016)	(0.861)	(0.018)
Number of Mortgages 90+ DPDs	-0.167	-0.344***	-0.329	-0.337***	0.009	-0.533***
	(0.519)	(0.023)	(0.582)	(0.023)	(1.133)	(0.027)
Number of Mortgages with Loan Mod	-0.088	-0.100***	-0.040	-0.086***	0.018	-0.144***
	(0.119)	(0.005)	(0.135)	(0.005)	(0.256)	(0.006)
Number of Open Mortgages	-0.226	-0.409***	-0.070	-0.367***	0.212	-0.559***
	(0.321)	(0.014)	(0.349)	(0.014)	(0.715)	(0.016)
Open Mortgage Balance / RIS Amount	-0.004	-0.424***	0.341	-0.384***	-0.590	-0.618***
	(0.898)	(0.043)	(1.030)	(0.034)	(1.803)	(0.043)

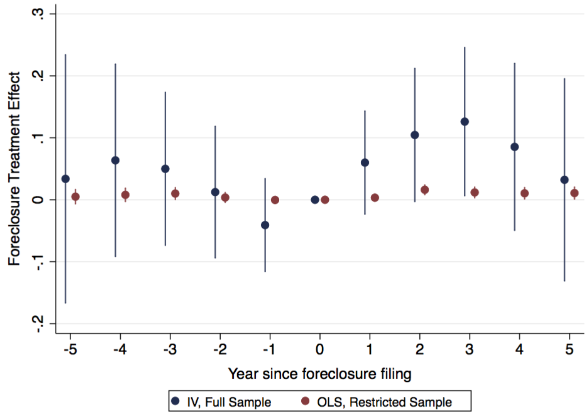
Notes: This table shows PSM and IV results for landlords for years 3 and 4 relative to the base year as in Table 7 for three different foreclosure definitions. The first two columns labeled "Court Decision" uses the foreclosure definition of a foreclosure occurring within three years of filing according to the court records. The second two columns labeled "Corelogic Deeds" uses a definition based on whether we observe a foreclosure in the CoreLogic deeds data within three years of the initial court filing rather than using court records of a foreclosure occurring. The third two columns labeled "Moved or Not" uses a definition based on whether we observe a sale (foreclosure or non-foreclosure) in the deeds data within three years of the initial court filing. For all three definitions, we re-create the judge leniency instrument using the new foreclosure definition. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.6: Treatment Effect Summary using Alternative Definitions of Foreclosure, Renter

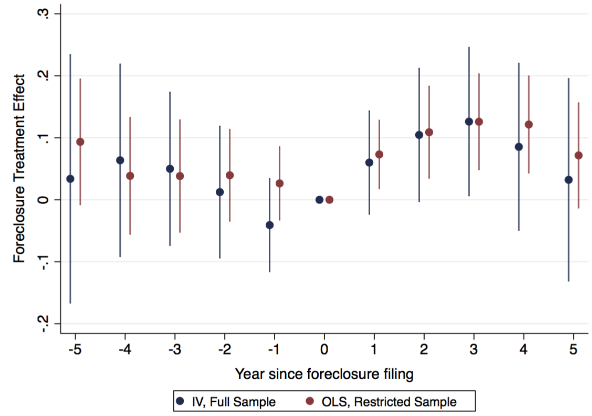
Foreclosure Definition:	Court Decision		Corelogic Deeds		Moved or Not	
Specification:	IV	PSM	IV	PSM	IV	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Moved from Foreclosure Address	0.107*	0.005	0.130	0.011**	0.216	0.009*
	(0.063)	(0.005)	(0.094)	(0.005)	(0.185)	(0.005)
Cumulative Number of Moves	0.125	0.005	0.161	0.013**	0.272	0.011
	(0.084)	(0.006)	(0.125)	(0.006)	(0.242)	(0.007)
Owns Primary Residence	0.021	-0.013	0.123	-0.037**	0.117	0.021
	(0.061)	(0.013)	(0.091)	(0.016)	(0.255)	(0.018)
Log Square Footage of Living Space	-0.080*	0.004	-0.113*	0.001	-0.133	0.002
	(0.048)	(0.004)	(0.065)	(0.004)	(0.095)	(0.005)
Log Zip Code Average Income	-0.044	-0.004**	-0.082	-0.003*	-0.113	-0.002
	(0.032)	(0.002)	(0.052)	(0.002)	(0.096)	(0.002)
Elementary School Test Score Rank	-3.737	-0.154	-2.757	0.022	-20.040	-0.164
	(2.416)	(0.147)	(2.163)	(0.149)	(15.850)	(0.173)
Middle School Test Score Rank	2.251	-0.057	3.843	-0.257	3.580	-0.096
	(2.769)	(0.156)	(5.444)	(0.159)	(11.497)	(0.178)
High School Test Score Rank	0.253	-0.363**	-0.563	-0.054	4.463	-0.221
	(2.288)	(0.176)	(2.708)	(0.171)	(7.902)	(0.195)
Cumulative Number of Divorces	0.005	-0.001	0.010	0.000	0.030	0.000
	(0.012)	(0.001)	(0.017)	(0.001)	(0.031)	(0.001)
Cumulative Number of Crimes Convicted	0.015	0.028***	0.148	0.018*	0.147	0.025**
	(0.102)	(0.010)	(0.165)	(0.010)	(0.188)	(0.011)
Cumulative Number of Bankruptcies	-0.007	-0.001	-0.021	-0.002	-0.041	-0.001
	(0.015)	(0.001)	(0.022)	(0.001)	(0.043)	(0.001)
Cumulative Number of DUI Convictions	0.005	0.000	0.004	-0.000	0.042*	0.001
	(0.009)	(0.001)	(0.014)	(0.001)	(0.025)	(0.001)
VantageScore	-5.913	0.208	-54.063	-1.268	-58.466	6.037*
	(41.752)	(2.776)	(37.584)	(2.743)	(60.925)	(3.248)
Death	0.021	-0.002	0.039	0.000	0.018	0.000
	(0.023)	(0.002)	(0.032)	(0.002)	(0.043)	(0.002)
Number of Foreclosures	0.016	-0.003	0.021	0.001	0.003	-0.004
	(0.035)	(0.004)	(0.041)	(0.004)	(0.068)	(0.004)
Number of Unpaid Collections	1.189	0.164*	0.909	0.120	1.091	0.060
	(0.778)	(0.088)	(0.909)	(0.087)	(1.532)	(0.099)
Number of Auto Loans	0.156	0.008	0.124	-0.006	0.291	0.000
	(0.222)	(0.020)	(0.245)	(0.020)	(0.405)	(0.023)
Number of Mortgages 90+ DPDs	0.196	0.028	0.156	0.034	0.327	0.037
	(0.254)	(0.028)	(0.298)	(0.027)	(0.524)	(0.034)
Number of Mortgages with Loan Mod	0.011	0.000	0.014	0.000	-0.006	0.001
	(0.017)	(0.002)	(0.027)	(0.002)	(0.033)	(0.002)
Number of Open Mortgages	-0.158*	0.002	-0.139	-0.003	-0.362**	0.007
	(0.084)	(0.007)	(0.107)	(0.007)	(0.182)	(0.007)
Open Mortgage Balance / RIS Amount	0.021	-0.002	0.116	-0.012	-0.296	-0.001
	(0.135)	(0.010)	(0.163)	(0.010)	(0.261)	(0.012)

Notes: This table shows PSM and IV results for renters for years 3 and 4 relative to the base year as in Table 7 for three different foreclosure definitions. The first two columns labeled ”Court Decision” uses the foreclosure definition of a foreclosure occurring within three years of filing according to the court records. The second two columns labeled ”Corelogic Deeds” uses a definition based on whether we observe a foreclosure in the CoreLogic deeds data within three years of the initial court filing rather than using court records of a foreclosure occurring. The third two columns labeled ”Moved or Not” uses a definition based on whether we observe a sale (foreclosure or non-foreclosure) in the deeds data within three years of the initial court filing. For all three definitions, we re-create the judge leniency instrument using the new foreclosure definition. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure A.6: Renters Moved Heterogeneity



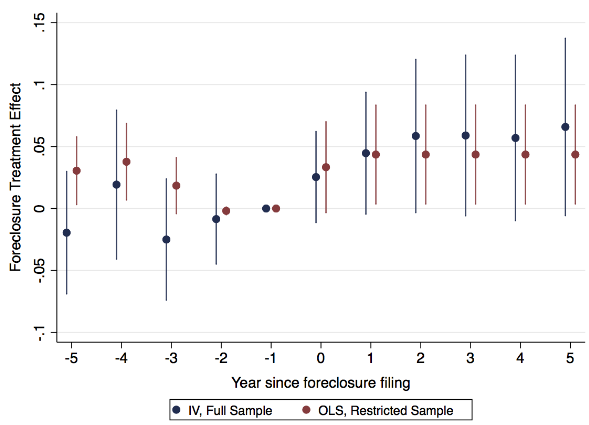
(a) Black Renters, Any Landlords



(b) Black Renters, White Landlords

Notes: These two figures illustrate the treatment effect of foreclosure on the probability of moving out of the foreclosed-upon property for black renters. Panel (a) does not condition on landlords' characteristics, whereas Panel (b) restricts to cases with only white landlords.

Figure A.7: Landlords DUI Heterogeneity



(a) Cumulative Number of DUI Convictions

Notes: This figure displays the treatment effects of foreclosure on cumulative number of DUI convictions for landlords, using full IV sample (blue) and restricted OLS subsample (red). To reconcile the difference in the IV and PSM estimates in Figure 12c, we condition cases on having strictly one young landlord, i.e., age below the median age across all landlords, and having no renters living at the property at the time of foreclosure filing. These landlords must also have strictly one open mortgage one and total mortgage balance as a fraction of the original complaint amount less than 1.4 at one year prior to foreclosure filing. This original complaint amount must also be greater than $210,000. These restrictions leave 459 case-landlords in the final OLS subsample.

D.2 Non-Court-Based Foreclosure Outcomes

One potential concern is that our court-based foreclosure measure has measurement error either due to un-recorded judgements or due to errors in our attempt to identify foreclosures. Tables A.4, A.5, and A.6 show results for years 3 and 4 relative to the base year as in Table 7 with three different foreclosure outcomes. The first outcome is our standard outcome of foreclosure within three years according to the court judgements data. The second and third outcomes are robustness checks that code a foreclosure as occurring if we observe a foreclosure or a move within three years in the CoreLogic deeds data. We re-estimate propensity scores based on the new foreclosure definition for PSM and re-estimate judge leniency using the new foreclosure definition for IV.

One can see that the results are highly consistent with our main court-decision-based measure of foreclosure. That being said, the instrument is more precise with the court data. These robustness checks show that our results are not driven by how we define foreclosure in the court data.

D.3 Disentangling Foreclosure From Time To Foreclosure

One potential concern is that our foreclosure measure is picking up something else. This is particularly a concern for IV because all of our variation is at the judge level and it might be the case that judges who are more or less likely to foreclose also do other things that are actually causing our measured effects. The most natural such story is that judges that do not foreclose take longer to decide the foreclosure case and that it is the longer time in which the case is being processed that gives the owner, renter, or landlord breathing room and improves the outcomes. In this Appendix we test this alternate story and find no evidence to substantiate it: foreclosure matters, not time to foreclosure.

To reach this conclusion, we first define the length of a case as the difference between the date of the last and first judgement on the case. The median judgement takes about one year, so we use an indicator for whether a case takes over a year as our main outcome variable. Our results are robust to using two or three years as the measure of case length.

We then augment our main IV and PSM empirical approaches to have the key independent variables be both the foreclosure within three years indicator and the case lasting over one year indicator. In particular, the OLS regression we want to estimate instead of (1) is:

$$Y_{i,k,s,t} = \beta_s^F F_k + \beta_s^L L_k + \gamma_s X_i + \xi_{m(k),s} + \phi_{z(k),t,s} + \varepsilon_{i,m,s,t}. \tag{6}$$

L_k is the indicator for the case taking more than one year to resolve, β_s^F is the measured coefficient on foreclosure over horizon s, and β_s^L is the coefficient on the length of the case over horizon s. One can see from this regression that the concern is that F_k and L_k are correlated and that by omitting L_k we had a biased coefficient on F_k.

Of course, we have the same concerns about OLS that we had in the main text. We thus augment our IV and PSM methods to account for these issues. For IV, we define a leave out average of length just as we defined a leave out average of foreclosure to measure leniency. Define the leniency Z of case k assigned to calendar c in year t as:

$$Z^L_{k,c,t} = \frac{\sum_{j \in c,t,j \neq k} L_{j,c,t}}{N_{(-k),c,t}},$$

while the corresponding foreclosure definition remains:

$$Z^F_{k,c,t} = \frac{\sum_{j \in c,t,j \neq k} F_{j,c,t}}{N_{(-k),c,t}}.$$

We then use the instrument to estimate the causal effect of foreclosure in a two-stage least squares framework for $s = -5, ..., 5$:

$$Y_{i,k,s,t} = \beta^F_s F_k + \beta^L_s L_k + \gamma_s X_i + \xi_{m(k),s} + \phi_{z(k),t,s} + \varepsilon_{i,k,s,t} \tag{7}$$

$$F_k = \Gamma^F Z^F_{k,c,t} + \Gamma^L Z^L_{k,c,t} + \alpha X_i + \zeta_{m(k)} + \varphi_{z(k),t} + e_{i,k,t} \tag{8}$$

$$L_k = \Omega^F Z^F_{k,c,t} + \Omega^L Z^L_{k,c,t} + \alpha X_i + \zeta_{m(k)} + \varphi_{z(k),t} + e_{i,k,t}, \tag{9}$$

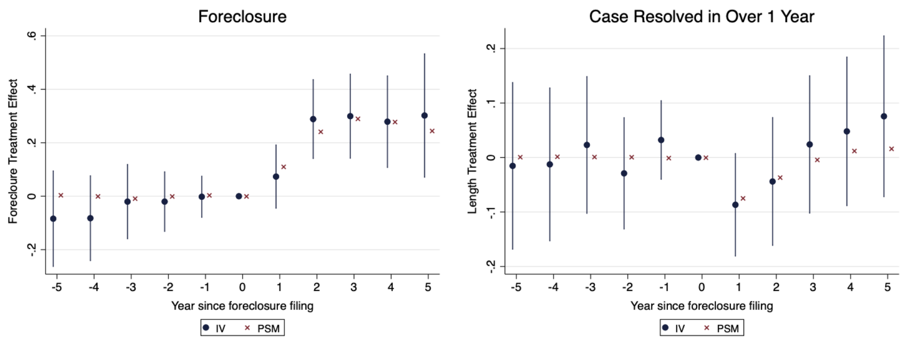
where equations (8) and (9) are both first stage equations. Intuitively, we are using two separate judge leniency measures, one relating to foreclosure and one relating to case length, and using these two variables to instrument both foreclosure and the case length indicator. This approach uses is variation in case length and foreclosure leniency that is orthogonal across judges to identify each coefficient separately. We cluster and weight these regressions as in the main text.

For our PSM approach, we are still concerned about cases that are deferentially likely to foreclose and are not as concerned about cases being observably different with regards to how long they will take. We thus use the same PSM procedure as before that creates deciles of the predicted foreclosure probability and conditions the fixed effects on these deciles as well. Thus our PSM approach is:

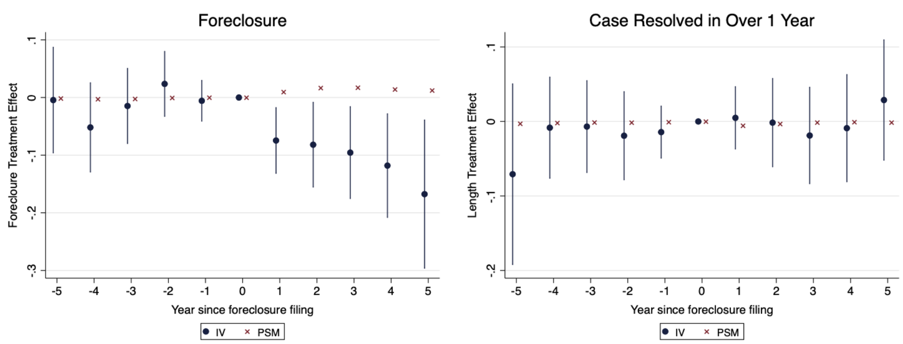
$$Y_{i,k,s,t,p} = \beta^F_s F_k + \beta^L_s L_k + \gamma_s X_i + \xi_{m(k),s,p} + \phi_{z(k),s,t,p} + \varepsilon_{i,k,s,t,p}, \tag{10}$$

where the propensity score bins continue to be estimate by equation (5). Again, we cluster and

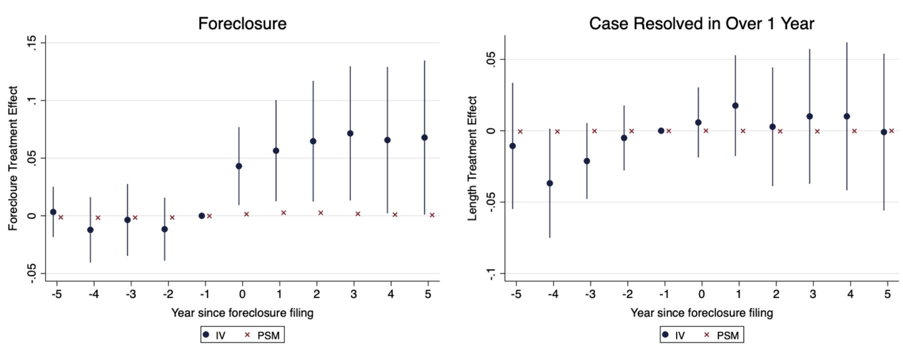
Figure A.8: Foreclosure vs. Length to Foreclosure For Selected Owner Outcomes



(a) Moved from Foreclosure Address



(b) Log Zip Code Average Income



(c) Cumulative Number of Divorces

Notes: Each panel shows IV and PSM results for the indicated outcome variable for all owners in our sample. The left panel show foreclosure outcomes, while the right panel show outcomes for the case lasting more than one year. Each dot indicates the IV point estimate for β_s^F or β_s^L estimated using equations (7), (8), and (9) and the bars indicate 95% confidence intervals. Each x indicates the PSM estimate for β_s^F or β_s^L estimated using equation (10). PSM confidence intervals are small enough that they are not shown. Standard errors are clustered by case, and regressions are weighted by the inverse of the number of people in each case.

Table A.7: Treatment Effects of Foreclosure and Time to Foreclosure Summary, Owners

Specification:	IV Baseline	IV Both		PSM Baseline	PSM Both	
Coefficient:	Foreclosure	Foreclosure	Case Length	Foreclosure	Foreclosure	Case Length
	(1)	(2)	(3)	(4)	(5)	(6)
Moved from Foreclosure Address	0.289***	0.290***	0.036	0.285***	0.285***	0.004
	(0.081)	(0.081)	(0.065)	(0.003)	(0.003)	(0.002)
Cumulative Number of Moves	0.390***	0.390***	-0.009	0.352***	0.354***	-0.013***
	(0.110)	(0.110)	(0.089)	(0.004)	(0.004)	(0.003)
Owns Primary Residence	-0.220**	-0.218**	-0.026	-0.166***	-0.167***	0.003
	(0.106)	(0.106)	(0.081)	(0.004)	(0.004)	(0.003)
Log Square Footage of Living Space	-0.021	-0.018	0.033	0.022***	0.022***	-0.001
	(0.051)	(0.051)	(0.041)	(0.002)	(0.002)	(0.002)
Log Zip Code Average Income	-0.106**	-0.106**	-0.014	0.016***	0.016***	-0.001
	(0.041)	(0.041)	(0.034)	(0.001)	(0.001)	(0.001)
Elementary School Test Score Rank	-3.282	-3.097	1.511	0.712***	0.741***	-0.211***
	(2.769)	(2.830)	(2.111)	(0.097)	(0.097)	(0.082)
Middle School Test Score Rank	-6.143**	-6.003**	2.369	0.101	0.105	-0.031
	(2.851)	(2.879)	(2.270)	(0.088)	(0.089)	(0.074)
High School Test Score Rank	-3.025	-2.892	1.946	0.987***	0.998***	-0.078
	(3.107)	(3.141)	(2.483)	(0.101)	(0.102)	(0.086)
Cumulative Number of Divorces	0.065**	0.069**	0.010	0.002*	0.002*	-0.000
	(0.028)	(0.030)	(0.025)	(0.001)	(0.001)	(0.001)
Cumulative Number of Crimes Convicted	0.023	-0.058	-0.231**	0.005	0.004	0.006*
	(0.100)	(0.109)	(0.110)	(0.004)	(0.004)	(0.003)
Cumulative Number of Bankruptcies	0.027	0.028	0.020	0.006***	0.002	0.034***
	(0.048)	(0.048)	(0.040)	(0.002)	(0.002)	(0.001)
Cumulative Number of DUI Convictions	0.017	0.005	-0.039	-0.001	-0.001	0.000
	(0.022)	(0.025)	(0.025)	(0.001)	(0.001)	(0.001)
VantageScore	-13.866	-15.730	-35.605*	-3.538***	-3.126***	-2.983***
	(25.752)	(26.115)	(20.575)	(0.733)	(0.738)	(0.670)
Death	0.006	0.008	0.042*	0.008***	0.008***	-0.000
	(0.026)	(0.026)	(0.024)	(0.001)	(0.001)	(0.001)
Number of Foreclosures	0.085	0.089	0.101	0.210***	0.209***	0.007**
	(0.097)	(0.097)	(0.091)	(0.003)	(0.003)	(0.003)
Number of Unpaid Collections	1.250*	1.245*	-0.106	0.375***	0.380***	-0.039**
	(0.666)	(0.671)	(0.609)	(0.021)	(0.022)	(0.020)
Number of Auto Loans	-0.152	-0.166	-0.300*	-0.022***	-0.016**	-0.043***
	(0.210)	(0.213)	(0.180)	(0.006)	(0.006)	(0.006)
Number of Mortgages 90+ DPDs	-0.288	-0.289	-0.026	-0.248***	-0.255***	0.049***
	(0.246)	(0.248)	(0.214)	(0.007)	(0.007)	(0.007)
Number of Mortgages with Loan Mod	0.036	0.034	-0.057	-0.099***	-0.098***	-0.009***
	(0.053)	(0.054)	(0.043)	(0.001)	(0.001)	(0.002)
Number of Open Mortgages	-0.260***	-0.259***	0.024	-0.310***	-0.304***	-0.041***
	(0.095)	(0.096)	(0.085)	(0.003)	(0.003)	(0.003)
Open Mortgage Balance / RIS Amount	-0.416***	-0.413***	0.063	-0.307***	-0.303***	-0.028***
	(0.157)	(0.158)	(0.141)	(0.006)	(0.006)	(0.006)

Notes: This table shows PSM and IV results for owners for years 3 and 4 relative to the base year as in Table 7 for the baseline IV and PSM models (columns 1 and 4) and for models with both foreclosure and case length being over 1 year both included as regressors (columns 2, 3, 5, and 6). All regressions are weighted by the inverse number of people per case. All standard errors are clustered by case. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.8: Treatment Effects of Foreclosure and Time to Foreclosure Summary, Landlords

Specification:	IV Baseline	IV Both		PSM Baseline	PSM Both	
Coefficient:	Foreclosure	Foreclosure	Case Length	Foreclosure	Foreclosure	Case Length
	(1)	(2)	(3)	(4)	(5)	(6)
Moved from Foreclosure Address	0.050	0.002	-0.087	0.017***	0.017***	0.004
	(0.161)	(0.189)	(0.113)	(0.006)	(0.006)	(0.006)
Cumulative Number of Moves	-0.042	-0.096	-0.097	0.031***	0.031***	0.005
	(0.235)	(0.278)	(0.167)	(0.008)	(0.008)	(0.008)
Owns Primary Residence	0.339*	0.328	-0.020	0.027	0.028	-0.001
	(0.204)	(0.243)	(0.157)	(0.036)	(0.036)	(0.025)
Log Square Footage of Living Space	-0.106	-0.166	-0.150	-0.009	-0.009	-0.004
	(0.117)	(0.143)	(0.099)	(0.007)	(0.007)	(0.007)
Log Zip Code Average Income	0.127	0.151	0.049	-0.004	-0.004	-0.003
	(0.088)	(0.106)	(0.065)	(0.003)	(0.003)	(0.003)
Elementary School Test Score Rank	0.324	1.881	2.001	0.045	0.058	-0.187
	(6.803)	(8.100)	(3.748)	(0.310)	(0.311)	(0.310)
Middle School Test Score Rank	-6.317	-7.967	-4.256	0.001	0.031	-0.375*
	(5.583)	(6.267)	(3.821)	(0.197)	(0.198)	(0.200)
High School Test Score Rank	-6.568	-11.005	-9.763**	-0.085	-0.063	-0.265
	(5.884)	(7.168)	(4.692)	(0.226)	(0.227)	(0.224)
Cumulative Number of Divorces	-0.065	-0.089	-0.033	-0.001	-0.001	0.001
	(0.051)	(0.068)	(0.042)	(0.002)	(0.002)	(0.002)
Cumulative Number of Crimes Convicted	0.157	0.132	-0.041	0.008	0.008	0.003
	(0.181)	(0.218)	(0.172)	(0.009)	(0.009)	(0.009)
Cumulative Number of Bankruptcies	0.095	0.134	0.070	0.015***	0.012***	0.032***
	(0.127)	(0.141)	(0.086)	(0.004)	(0.004)	(0.005)
Cumulative Number of DUI Convictions	0.058*	0.053	-0.007	0.003**	0.003**	0.000
	(0.033)	(0.040)	(0.028)	(0.001)	(0.001)	(0.001)
VantageScore	10.422	3.792	-14.722	2.909*	3.369**	-6.044***
	(36.319)	(43.025)	(28.951)	(1.526)	(1.526)	(1.578)
Death	0.022	0.029	0.014	0.002	0.002	0.001
	(0.039)	(0.047)	(0.032)	(0.002)	(0.002)	(0.002)
Number of Foreclosures	0.055	0.128	0.165	0.325***	0.326***	-0.016
	(0.492)	(0.591)	(0.511)	(0.021)	(0.021)	(0.022)
Number of Unpaid Collections	0.379	0.525	0.320	0.264***	0.253***	0.152***
	(1.198)	(1.384)	(1.051)	(0.053)	(0.054)	(0.053)
Number of Auto Loans	-0.324	-0.383	-0.129	0.016	0.017	-0.023
	(0.409)	(0.491)	(0.333)	(0.017)	(0.017)	(0.017)
Number of Mortgages 90+ DPDs	-0.167	0.195	0.807	-0.344***	-0.350***	0.079***
	(0.519)	(0.663)	(0.522)	(0.023)	(0.023)	(0.023)
Number of Mortgages with Loan Mod	-0.088	-0.097	-0.020	-0.100***	-0.100***	-0.008
	(0.119)	(0.140)	(0.091)	(0.005)	(0.005)	(0.005)
Number of Open Mortgages	-0.226	-0.225	0.003	-0.409***	-0.408***	-0.017
	(0.321)	(0.386)	(0.290)	(0.014)	(0.014)	(0.014)
Open Mortgage Balance / RIS Amount	-0.004	0.335	0.756	-0.424***	-0.421***	-0.047
	(0.898)	(1.194)	(0.771)	(0.043)	(0.045)	(0.036)

Notes: This table shows PSM and IV results for landlords for years 3 and 4 relative to the base year as in Table 7 for the baseline IV and PSM models (columns 1 and 4) and for models with both foreclosure and case length being over 1 year both included as regressors (columns 2, 3, 5, and 6). All regressions are weighted by the inverse number of people per case. All standard errors are clustered by case. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.9: Treatment Effects of Foreclosure and Time to Foreclosure Summary, Renters

Specification:	IV Baseline	IV Both		PSM Baseline	PSM Both	
Coefficient:	Foreclosure	Foreclosure	Case Length	Foreclosure	Foreclosure	Case Length
	(1)	(2)	(3)	(4)	(5)	(6)
Moved from Foreclosure Address	0.107*	0.136*	0.088	0.005	0.005	0.009*
	(0.063)	(0.071)	(0.063)	(0.005)	(0.005)	(0.005)
Cumulative Number of Moves	0.125	0.164*	0.119	0.005	0.005	0.010
	(0.084)	(0.094)	(0.083)	(0.006)	(0.006)	(0.006)
Owns Primary Residence	0.021	0.010	-0.037	-0.013	-0.013	-0.016
	(0.061)	(0.065)	(0.050)	(0.013)	(0.013)	(0.012)
Log Square Footage of Living Space	-0.080*	-0.085	-0.011	0.004	0.004	-0.000
	(0.048)	(0.066)	(0.069)	(0.004)	(0.004)	(0.004)
Log Zip Code Average Income	-0.044	-0.050	-0.019	-0.004**	-0.004**	-0.002
	(0.032)	(0.035)	(0.026)	(0.002)	(0.002)	(0.002)
Elementary School Test Score Rank	-3.737	-4.244*	-1.921	-0.154	-0.165	0.278*
	(2.416)	(2.452)	(1.507)	(0.147)	(0.148)	(0.153)
Middle School Test Score Rank	2.251	2.559	1.174	-0.057	-0.048	-0.326*
	(2.769)	(2.789)	(1.518)	(0.156)	(0.156)	(0.169)
High School Test Score Rank	0.253	-1.136	-3.417	-0.363**	-0.373**	0.380**
	(2.288)	(2.421)	(2.565)	(0.176)	(0.176)	(0.182)
Cumulative Number of Divorces	0.005	0.000	-0.010	-0.001	-0.001	0.001
	(0.012)	(0.014)	(0.012)	(0.001)	(0.001)	(0.001)
Cumulative Number of Crimes Convicted	0.015	0.085	0.171*	0.028***	0.028***	0.001
	(0.102)	(0.114)	(0.096)	(0.010)	(0.010)	(0.010)
Cumulative Number of Bankruptcies	-0.007	-0.009	-0.006	-0.001	-0.001	0.001
	(0.015)	(0.016)	(0.016)	(0.001)	(0.001)	(0.001)
Cumulative Number of DUI Convictions	0.005	0.001	-0.012	0.000	0.000	0.000
	(0.009)	(0.010)	(0.013)	(0.001)	(0.001)	(0.001)
VantageScore	-5.913	27.903	74.575**	0.208	0.237	-6.474**
	(41.752)	(49.766)	(35.549)	(2.776)	(2.776)	(2.927)
Death	0.021	0.002	-0.042	-0.002	-0.002	0.004*
	(0.023)	(0.027)	(0.026)	(0.002)	(0.002)	(0.002)
Number of Foreclosures	0.016	0.013	-0.007	-0.003	-0.003	0.002
	(0.035)	(0.042)	(0.040)	(0.004)	(0.004)	(0.003)
Number of Unpaid Collections	1.189	1.393	0.450	0.164*	0.164*	-0.027
	(0.778)	(0.909)	(0.860)	(0.088)	(0.088)	(0.095)
Number of Auto Loans	0.156	0.082	-0.164	0.008	0.008	-0.000
	(0.222)	(0.253)	(0.215)	(0.020)	(0.020)	(0.021)
Number of Mortgages 90+ DPDs	0.196	0.078	-0.259	0.028	0.028	0.026
	(0.254)	(0.300)	(0.273)	(0.028)	(0.028)	(0.030)
Number of Mortgages with Loan Mod	0.011	0.013	0.003	0.000	0.000	0.001
	(0.017)	(0.019)	(0.020)	(0.002)	(0.002)	(0.002)
Number of Open Mortgages	-0.158*	-0.215**	-0.126	0.002	0.002	-0.009
	(0.084)	(0.102)	(0.096)	(0.007)	(0.007)	(0.007)
Open Mortgage Balance / RIS Amount	0.021	-0.057	-0.174	-0.002	-0.002	-0.015
	(0.135)	(0.148)	(0.111)	(0.010)	(0.010)	(0.009)

Notes: This table shows PSM and IV results for renters for years 3 and 4 relative to the base year as in Table 7 for the baseline IV and PSM models (columns 1 and 4) and for models with both foreclosure and case length being over 1 year both included as regressors (columns 2, 3, 5, and 6). All standard errors are clustered by case. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

weight these regressions as in the main text.

Figure A.8 shows results for three key outcomes for owners: moving, neighborhood quality for owners, and divorce. For each outcome, the left panel shows the coefficients on foreclosure β_s^F while the right hand panel shows the coefficients on whether the case is resolved in over one year β_s^L. Three things are of note. First, the confidence intervals on foreclosure are somewhat wider. Second, the point estimates for foreclosure are very close to our main results, indicating that the effects really were due to foreclosure not case length. Third, the effects of a longer case are near zero with one exception: for moving, cases that take over a year to resolve see a decline in moving in year one that then goes away. This makes sense given that the foreclosure takes longer to be decided.

Tables A.7, A.8, and A.9 show pooled results for all outcomes for years 3 and 4 results for our main specification (same as Table 7) and the specification with both foreclosure and length of case for owners, renters, and landlords, respectively. One can see that for both IV and OLS, adding in case length does not significantly alter our results for foreclosure for essentially all outcomes. We can also see that case length generally has economically insignificant effects. The exception is credit score, where it seems like a longer case leads to a lower credit score.

Overall, our analysis of time to foreclosure indicates it is far less important than the main foreclosure outcome. This throws cold water on the notion that our foreclosure effects were actually picking up effects for case length.

E Additional Background

E.1 Divorce Laws in Illinois

For contested divorces, Illinois is an "equitable division" state, meaning that the marital assets are divided "equitably" rather than 50/50. The judge weighs factors like length of marriage, financial resources of both spouses, employability of the spouses, and the spouses' contribution to the acquisition of the property. Assets are classified as either "marital property" belonging to both spouses or "separate property" belonging to an individual. Marital property is acquired during the marriage, and separate property is from before the marriage. Gifts given to one spouse count as separate property as long as it is not commingled with other assets belonging to both spouses, such as by putting the funds in a joint bank account. These rules apply only to contested divorces. For uncontested divorces, all property may be split however the spouses want.

In a contested divorce, the spouse with primary custody of the children often gets to keep the house (Anderson and Associates (2015)). Sometimes the award is temporary and the house must be sold once the youngest child turns 18. Even if a spouse is given the home, they may still be required to buy out the partner's interest, or the higher-earning spouse may continue to be required to pay the mortgage as part of a support arrangement.

E.1.1 Property Held in Trusts

The house does not count as marital property if the spouse is a beneficiary of a revocable trust because the control of the property is with the grantor. If the spouse is a beneficiary of a irrevocable trust, then the property does not count as marital property as long as the property is not mingled with marital property. If the spouse is a grantor of a revocable trust, then the property counts as marital property, unless it was acquired prior to the marriage or was a gift given to only one spouse and not commingled. Income derived from a trust does count toward the income of the beneficiary spouse (Law Offices of Schlesinger and Strauss (2017), Mirabella, Kincaid, Frederick, Miarabella (2015)).