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A Shortage of Short Sales: Explaining the Underutilization of a Foreclosure Alternative

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A Shortage of Short Sales: Explaining the Underutilization of a Foreclosure Alternative

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Abstract

The Great Recession led to widespread mortgage defaults, with borrowers resorting to both foreclosures and short sales to resolve their defaults. I first quantify the economic impact of foreclosures relative to short sales by comparing the home price implications of both. After accounting for omitted variable bias, I find that homes selling as short sales transact at 9.2% to 10.5% higher prices on average than those that sell after foreclosure. Short sales also exert smaller negative externalities than foreclosures, with one short sale decreasing nearby property values by 1 percentage point less than a foreclosure. So why weren't short sales more prevalent? These home price benefits did not increase the prevalence of short sales because free rents during foreclosures caused more borrowers to select foreclosures, even though higher advances led servicers to prefer more short sales. In states with longer foreclosure timelines, the benefits from foreclosures increased for borrowers, so short sales were less utilized. I find that one standard deviation increase in the average length of the foreclosure process decreased the short sale share by 0.35 to 0.45 standard deviation. My results suggest that policies that increase the relative attractiveness of short sales could help stabilize distressed housing markets.

Keywords: foreclosures, short sales, externalities, home prices, mortgage servicing

JEL Classification: D14, G01, G21, R31

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1 Introduction

The housing market crash from 2007 to 2012 led to high foreclosure rates throughout the country. As borrowers became delinquent and home price declines led to negative equity, many borrowers lost their homes to foreclosure. Statistics from RealtyTrac indicate that between 2007 and 2011, there were over 4 million completed foreclosures. The flood of foreclosures also led to high rates of foreclosed homes being sold, with 29% of all homes sold in 2009 being foreclosure sales, and over 60% of them in the hardest hit states.^{1,2} Besides facing foreclosure, delinquent borrowers could also resolve their default via short sales. Figure 1 plots data from DataQuick in 10 large metropolitan statistical areas (MSAs) across the country showing the total number of short sales and foreclosure sales per quarter. While foreclosures increased dramatically during the housing crash, short sales were also utilized, especially later in the crisis. Despite the rise in both types of distress sales, the causes and economic impacts — both positive and negative — of short sales are less understood.³

The economic importance of short sales is highlighted by multiple government programs, including the Home Affordable Foreclosure Alternatives (HAFA) program, which aimed to promote more short sales by offering financial incentives to the agents in charge of making the short sale decision.⁴ The offering of incentives to encourage more short sales suggests that there might be efficiency gains from short sales over foreclosures. However, these efficiency gains have not been well quantified because of the nonrandom assignment of short sales. There is endogenous selection into short sales for delinquent borrowers based on unobservable characteristics such as home quality at the time of initial delinquency. In addition, when testing for factors that drive short sale behavior, such as the foreclosure timeline, endogeneity is also a problem. Challenges arise because of reverse causality between the factors driving short sales and the short sales themselves and omitted variable bias resulting from unobservable conditions driving both short sales and these factors.

This is the first paper that combines multiple nationally representative data sets with identifi-

¹Foreclosure statistics come from <http://www.realtytrac.com/content/news-and-opinion/slideshow-2012-foreclosure-market-outlook-7021> and <http://www.realtytrac.com/news/realtytrac-reports/2010-year-end-and-q4-foreclosure-sales-report/>.

²For the rest of this paper, I define a *foreclosure sale* as a sale of a home that had just been foreclosed on to a third party. The foreclosure sale could have taken place as a foreclosure auction or as a sale on a real estate-owned (REO) property, which is a property owned by the lender.

³I use the term *distress sale* to refer to either a short sale or a foreclosure sale for the rest of this paper.

⁴The money used to fund HAFA came from the Troubled Asset Relief Program (TARP). As of June 30, 2014, \$804 million of TARP money was spent on HAFA.

cation strategies to address these problems of endogeneity. I begin by using transactions data from 10 large MSAs to examine how the transaction price differs when a home is sold as a short sale compared with being sold after a foreclosure. I find that, although short sales were less common than foreclosures, they were actually more beneficial for home prices and the housing market. However, omitted variable bias could be present because of unobserved factors such as home quality at the time of delinquency, which impacts both selection into short sale and transaction prices. Lower-quality homes were more likely to be foreclosed on and to sell at lower prices.

I merge home transactions data with listings data to address the problem of omitted home quality in two ways. First, I distinguish if a foreclosed home was a result of a failed short sale by checking for a listing on that home prior to the completion of the foreclosure. I assume that the listing of a home helps control for home quality since homeowners who list their homes with an intent to sell are more likely to maintain their home to maximize the likelihood of a successful sale and to obtain a higher selling price. By comparing only these prelisted foreclosed homes with short sales, I am able to compare homes with similar quality. My results suggest that prelisted foreclosed homes sell at 2.1% higher prices than nonprelisted ones, but they still sell at 9.6% lower prices than short sales.

Listing is not a perfect control for home quality, so I exploit plausibly exogenous variation in the time of loan origination and home listing for borrowers who sell distressed homes in the same census tract and time as an instrument for the success of a short sale. For each home, I calculate the percentage of loan balance outstanding at the time of the listing by assuming constant amortization on a 30-year fixed rate mortgage. As a result, older loans will have smaller balances. Mortgage lenders are then more likely to approve of a short sale for loans with a smaller outstanding balance because they face smaller losses. My results show that foreclosure sales still transact at 10.4% lower prices than short sales. One concern about the instrument is that borrowers who took out loans later in the housing boom might be of lower quality and more likely to be foreclosed on and to neglect home maintenance. However, Palmer (2015) showed that home price changes explain more of the variation in default rates among different cohorts of borrowers than borrower quality due to looser lending conditions, which suggests that borrower quality may be exogenous to the success of a short sale. As an additional check, I focus only on loans that originated between the fourth quarter of 2007 and the end of 2011, a period of stricter lending conditions. I find similar results.

Since short sales and foreclosures have different impacts on the sale price of a home, I would also expect them to have different externalities on the price of nearby homes. I employ the same spatial difference-in-difference method used by Campbell, Giglio, and Pathak (2011) and Anenberg and Kung (2014) in studying the foreclosure externality to show that homes near foreclosure sales sell at lower prices relative to homes near short sales, with home prices being up to 1 percentage point lower for each nearby foreclosure sale relative to a nearby short sale.⁵ Using listing data again to compare prelisted foreclosures with short sales allows me to address omitted home quality and show that results are robust to differences in home quality.

If short sales were more beneficial for the recovery of the housing market, why weren't they more prevalent? I provide evidence that the tension between the agents who make the short sale decision and those who enjoy the benefits of higher home prices is one factor that can explain this discrepancy. In particular, neither of the two agents directly involved in the short sale decision making — the delinquent borrower and the servicer of the loan — benefit from higher home prices.⁶ Instead, during the foreclosure process, borrowers can live for free in their homes, and servicers can continue collecting servicing fees, but foreclosures can also delay the recovery of servicing advances — payments made to investors by the servicer to cover missed payments by the borrower. Longer foreclosure timelines make foreclosures even more attractive to borrowers because they can enjoy more free housing, but the effect on servicers is not obvious since there is an increase in both the servicing fees and waiting time to recover advances.

To test for the impact of foreclosure timelines on the probability of a short sale, I need to tackle endogeneity resulting from reverse causality between short sales and foreclosure timelines and omitted variable bias from unobserved local macroeconomic factors driving both short sale activity and foreclosure timelines. Therefore, I use a state's judicial foreclosure law as an instrument for the foreclosure timeline similar to Mian, Sufi, and Trebbi (2015). Pence (2006) first showed that state laws requiring judicial foreclosures increased the foreclosure timeline. The advantage of using these laws as an instrument is that their historical origins were not affected by different economic situations across states (Ghent (2013)). I find that a one standard deviation increase in

⁵While this spatial difference-in-difference specification has been used to study foreclosure externalities, it was based on the method used by Linden and Rockoff (2008) to show the impact of sex offenders on home prices.

⁶I focus on the servicer of the mortgage backed security (MBS) as the agent who must approve of short sales since the sample of mortgages I use to test for short sale unpopularity consists of only private-label securitized (PLS) loans. I go more into depth about the parties that approve short sales when discussing institutional details.

the foreclosure timeline causes a 0.35-0.45 standard deviation decrease in a state's short sale share of distressed sales. I then show that heterogeneity across borrowers and servicers significantly affects the impact of longer foreclosure timelines on short sales.

Because different types of borrowers and servicers respond differently to longer foreclosure timelines, it is also important to see if one side contributed more to the decrease in short sales arising from longer foreclosure timelines. To do so, I interact proxies for rent and advances with foreclosure timelines separately to test for the borrower and servicer channels. I find that both parties are responsive to foreclosure timelines but in opposite directions. Higher rents decrease a borrower's preference for short sales, while higher advances increase a servicer's preference.⁷

This paper has important implications for policies to help mitigate future negative home price shocks and stabilize the housing market. Based on my estimates of the difference in the discount and externalities between short sales and foreclosures, increasing short sales by just 5% between 2007 and 2011 would have saved the housing market up to \$6.4 billion. While HAFA was a move in the right direction by encouraging short sales, my research suggests that reducing foreclosure timelines is another possible method to increase short sales. If policymakers can quantify the additional benefits that foreclosures offer borrowers over short sales, they can offer similar benefits to incentivize more short sales. Also, since a successful short sale requires servicer approval, additional incentives could be offered to financial institutions to encourage them to approve more short sales, including changes in accounting rules. Higher short sale rates can help protect against the price-default spiral modeled by Guren and McQuade (2015), which would help dampen initial housing market shocks in future recessions.

The paper proceeds as follows. The rest of this section reviews the related literature. Section 2 examines the institutional details of short sales and compares the trade-off between foreclosures and short sales for both borrowers and servicers. Section 3 details the different data sources I use and presents summary statistics.⁸ Section 4 highlights the benefits of short sales by showing how these homes sell at higher prices and have a smaller negative impact on the prices of nearby homes. Section 5 explains why short sales were less prevalent by empirically testing for the impact

⁷Because I do not have data on servicing fees, my results only show that higher advances cause longer foreclosure timelines to increase a servicer's preference for short sales, but the net impact of longer foreclosure timelines may actually decrease a servicer's preference for short sales if the fees they can collect are higher.

⁸All data used in this paper are provided to me by the REFM Lab at the UC Berkeley Haas School of Business.

of foreclosure timelines on the probability of a short sale. Section 6 concludes the paper.

1.1 Related Literature

The research on short sales so far has been sparse compared with the work on foreclosures. Clauretie and Daneshvary (2011) and Daneshvary and Clauretie (2012) are the only two papers that study the differential home price impact of short sales, while there is a plethora of work that focuses on foreclosures.⁹ They find that short sales lead to higher transaction prices and lower negative externalities, but they do not address the endogenous selection problem arising from omitted variables. Also, their results are restricted only to the city of Las Vegas. My paper improves upon their work because my higher quality data allows me to use identification strategies to deal with omitted home quality, and my results are nationally representative.

Meanwhile, research on the causes of short sales is even more scant. Zhu and Pace (2015) is the only paper to document the factors that influence the probability of a short sale, but they cannot identify the channel driving this effect.¹⁰ Also, their data are restricted to only mortgages in cross-state MSAs, which is problematic and produces results that cannot be generalized.¹¹ Again, I am able to improve upon the past research on short sales by using better data to show that the borrower channel is more responsible for the decrease in short sales than the servicer channel and to generate results at the national level.

This paper highlights another consequence of longer foreclosure timelines — fewer short sales. Research has already found that longer foreclosure timelines increase foreclosures (Zhu and Pace (2011) and Chatterjee and Eyigungor (2015)), although Mian, Sufi, and Trebbi (2015) show that judicial states, where foreclosure timelines are longer, had lower foreclosure rates. As borrowers save

⁹Studies have looked into how foreclosures cause a discount in the transaction price (Clauretie and Daneshvary (2009), Campbell, Giglio, and Pathak (2011), and Harding, Rosenblatt, and Yao (2012)) and how they exert negative externalities by decreasing nearby home prices (Harding, Rosenblatt, and Yao (2009), Campbell, Giglio, and Pathak (2011), Anenberg and Kung (2014), Fisher, Lambie-Hanson, and Willen (2015), Hartley (2014), Gerardi, Rosenblatt, Willen, and Yao (2015). (2015), Mian, Sufi and Trebbi (2015)) and by increasing crime (Ellen, Laco, and Sharygin (2013)). The externalities are smaller when a single lender holds a large share of the outstanding mortgages in a neighborhood (Favara and Giannetti 2017).

¹⁰In comparison to lack of work on short sales, the causes of high foreclosure rates have been well documented both theoretically (Campbell and Cocco (2015) and Corbae and Quintin (2015)) and empirically (Foote, Gerardi, and Willen (2008), Bajari, Chu, and Park (2008), Ghent and Kudlyak (2011), and Palmer (2015)).

¹¹Usually, the main urban center is located entirely in one state, while the surrounding states only contain the peripheries of the city and the suburbs. For example, the majority of the Chicago MSA is located in Illinois, including the entire city of Chicago. The parts that extend into Indiana and Wisconsin are more rural and less densely populated. Also, cross-state MSAs exclude states with large real estate markets, such as California and Florida.

more on rent when timelines are longer, they can afford to pay off more of their nonmortgage debts (Calem, Jagtiani, and Lang (2014)), but they also can afford to spend additional time searching for high-paying jobs so employment decreases (Herkenhoff and Ohanian (2015)). Lastly, longer foreclosure timelines increase costs for lenders because they may have to cover missed property taxes, hazard insurance, and homeowner association payments, and they recover less at liquidation because of excess depreciation on homes (Cordell, Geng, Goodman, and Yang (2015) and Cordell and Lambie-Hanson (2016)).

2 Short Sale Details and Comparison with Foreclosure

2.1 Overview of a Short Sale

When homeowners were underwater on their mortgages and delinquent on their mortgage payments as a result of the housing crash and poor economic conditions, many turned to foreclosures. However, there exists an alternative to foreclosures for borrowers who are behind on their mortgage. Instead of letting the lender foreclose on their homes, borrowers also have the option to seek a short sale. In a short sale, the borrower sells his home for less than what he owes on his mortgage, and the lender releases the lien on that property. To begin, the borrower first contacts the lender to initiate the short sale procedure.¹² The borrower then works with a real estate agent to list the short sale. After an offer is received, the borrower must submit a short sale package containing a hardship letter showing why the borrower is seeking a short sale, other personal financial documents, and a signed purchase contract with the offer price to the lender, who then ultimately needs to approve the selling price for the sale to take place.

Beginning in 2009, in an effort to help promote short sales, the U.S. Department of the Treasury introduced HAFA, while government-sponsored enterprises (GSEs) issued their own version of HAFA. These programs offered incentives for both the borrower and the servicer to do more short sales. Borrowers could receive money for relocation assistance after a short sale, while servicers received financial compensation to approve a short sale. Borrowers were also freed from any form of recourse, regardless of the state foreclosure recourse laws.

¹²*Lender* is just a generic term for the agent approving the short sale decision. My focus in this paper will be on the servicer.

2.2 Comparison from a Borrower's Perspective

Borrowers face a trade-off between the long-term benefits from a short sale and the short-term benefits from a foreclosure. Contrary to popular belief, borrowers' FICO[®] scores fall by the same amount when doing a short sale or a foreclosure.^{13,14} However, borrowers are locked out of the mortgage market for less time after a short sale, so they can buy a new home sooner. Borrowers are allowed to obtain a new mortgage only two years after a short sale, while they must wait three to seven years after a foreclosure. Not having to face a deficiency judgment saves them money in the long term as well.

On the other hand, the biggest benefit of choosing a foreclosure over a short sale is that borrowers have the right to live for free in the home during the entire foreclosure process. They cannot be evicted until ownership of the home changes after the foreclosure process has been completed. For many borrowers who are going through financial distress, this immediate benefit will outweigh the long-term benefits of a short sale, particularly if it is hard for them to imagine buying a home again after having trouble making mortgage payments. As foreclosure timelines increase and it takes longer to finish the foreclosure process, this foreclosure benefit increases for the borrower.

2.3 Comparison from a Servicer's Perspective

The agent who makes the decision to approve a short sale varies depending on what happened to the loan after it was originated. Table 1 presents a comparison of the type of loans, who makes the short sale decision, and what factors influence their decision. Traditionally, the lending institution would keep the loan on its balance sheet so it is responsible for deciding whether to approve a short sale for these loans. However, during the housing boom, the majority of the loans made were securitized into mortgage backed securities (MBS). For a PLS mortgage, the servicer of the loan is the deciding party. For loans that were securitized by GSEs, the GSEs ultimately decide whether to approve a short sale.

The primary objective of the originating lenders and GSEs is to maximize the recovery value of the delinquent mortgages because they take the losses on the mortgages. They need to decide

¹³FICO[®] is a registered trademark of Fair Issac Corporation in the United States and in other countries.

¹⁴A study done by FICO[®] actually shows an equal decline in credit scores for short sales and foreclosures. See <http://www.fico.com/en/blogs/risk-compliance/research-looks-at-how-mortgage-delinquencies-affect-scores/>.

what option allows them to receive the highest selling price on the home. As I will show, since short sales sell on average for more than foreclosures, these agents had an incentive to approve more short sales. They would only opt for a foreclosure if the losses from a short sale were so large that they believe they would be more likely to get a higher selling price in the future when it came time to sell the foreclosed home.

Servicers of PLS mortgages do not directly gain from higher selling prices; instead, they generate income by collecting servicing fees. As foreclosure timelines increase, servicers may be able to collect more fees. At the same time, servicers have to make advances to cover the payments missed by the borrowers so the investors are still paid. While they recoup these advances when the home is liquidated, the advances still are costly if the servicer has to finance them by borrowing. Thus, servicers have to balance between maximizing their fees and minimizing their advances, especially when timelines are longer, and both increase. For this study, I focus my analysis on private-label servicers because the sample of loans used to study the impact of foreclosure timelines on short sales is composed of all PLS mortgages.

When there are multiple loans associated with one home, the servicer for each loan must approve the short sale for it to go through. In these situations, servicers on the second-lien loan may be more reluctant to approve, since they cannot recover their advances until the first lien is completely paid because of their junior position. Given how much prices fell, there was the risk that the selling price would not be high enough to compensate these servicers. To entice servicers of second liens to approve a short sale, all parties involved in the short sale need to negotiate a deal so that the servicers on the second liens can recover some money even if the proceeds from the short sale are not enough. HAFA and its GSE counterpart programs also provided financial compensation to servicers on junior liens to encourage them to approve more short sales.¹⁵

¹⁵While I do not directly analyze the role that second liens play, I do find that foreclosure sales and short sales have similar shares of loans with second liens — 57% compared with 64%.

3 Data

3.1 Home Transaction Data

The data used to test the effects of short sales and foreclosure on home prices come from DataQuick, which has transaction-level data on every home sold. The data have a variable to indicate whether a transaction is a short sale or a foreclosure sale. Foreclosure sales may either be the sale of the home to a third party at a foreclosure auction or the sale of the home to a third party after it has become REO. However, DataQuick does not use the transaction records to determine when a short sale took place. Instead, it uses a proprietary model to identify short sales. Using an approach of their own in which they indicate a home as being a short sale if the sale price is less than 90% of the outstanding loan balance, Ferreira and Gyourko (2015) were able to match DataQuick’s indicator 90% of the time. Thus, the DataQuick short sale flag appears to be reliable. Unfortunately, DataQuick only began reporting short sales beginning in 2004, so I use data from 2004 to 2013, which is when the data ends.

Another shortcoming of DataQuick is that I am unable to observe when a home started the foreclosure process; however, I can see when it became REO and when the REO was liquidated, which I label as the foreclosure sale in this paper. Since I will be analyzing the effects of short sales and foreclosure sales on home prices, I only need to observe when the homes were sold. Because of the vast amount of data, I limit myself to a nationally representative sample of transactions from 10 large MSAs across the country.¹⁶

Counts and summary statistics for the transactions of single-family residential homes are presented in Table 2.¹⁷ Panel A shows the number of short sales, foreclosure sales, and all sales in each MSA. While different MSAs had different ratios of short sales to foreclosure sales, all MSAs did have more foreclosure sales than short sales. Panel B shows that on average there was approximately one short sale for every two foreclosures. Panel B also compares property-level characteristics data for the two types of sales. Short sale homes were statistically different from foreclosure homes in that they sold for higher prices and were bigger and newer.

¹⁶See the data appendix for the entire data cleaning procedure.

¹⁷Single-family residential homes include duplexes, triplexes, and quadplexes. I run robustness checks using transactions from all home types in the Appendix. The mean effects are similar.

3.2 Merged Listing and Transaction Data

Listing data come from Multiple Listing Services (MLS) provided by Altos Research. Every week, Altos Research takes a snapshot of the homes listed for sale on MLS and records the information. It provides listing data for the same 10 MSAs in my transaction data, but the listing data do not begin until October 2007. From these weekly snapshots, I can identify when the homeowner is attempting to sell the home. For homes that went into foreclosure, it is possible to see if the borrower attempted to sell the home first by checking if a listing existed prior to the home becoming REO or selling it in a foreclosure auction, which will be the basis of the instrument I use to address omitted variable bias. I define a foreclosure home as “prelisted” if there was a listing up to two years before the foreclosure auction or REO date.

The listing data have the full address of each home, which allows me to merge it with the transactions data. I do the merge for single-family homes only because the apartment or unit numbers for multifamily buildings and condos are not consistently defined. The detailed merging procedures are documented in the data Appendix. Because the listing data do not begin until October 2007, the merged listing and transaction data I have will be smaller in size. Also, listing a home on MLS is not the only way for homeowners to sell their home, so a listing cannot be found for all transactions.

Table 3 presents counts and summary statistics for the merged data set. Panel A shows that pre-listing varied across the MSAs, while Panel B shows that on average, approximately 20% of all foreclosure sales had previously been listed before the foreclosure was completed. In terms of property characteristics, there is a statistically significant difference between foreclosed homes that were prelisted and those that were not. Homes that were prelisted were bigger and sold for higher prices after foreclosure. The fact that these two types of homes have observable differences may imply that they have different impacts on home prices.

3.3 Loan Performance, Borrower, and Geography-Level Data

The loan-level data that I use to test whether a delinquent mortgage ends in a foreclosure or short sale come from the ABSNet Loan Database (ABSNet). It contains loan and borrower characteristics at origination and monthly performance data on approximately 90% of all PLS mortgages. For

each loan, I can observe the monthly status — whether it is current, delinquent, or in distress. There are also dates for when a loan entered foreclosure, became an REO, or was liquidated. The data have a indicator variable for short sales, and I use the foreclosure start date, REO date, and liquidation date to generate an indicator variable for foreclosures.

I define the foreclosure timeline as the length of time between the beginning of foreclosure and when the home becomes REO or is sold at a foreclosure auction. Since the housing market crash began in 2007, I calculate the foreclosure timeline in 2007 by using only loans that began the foreclosure process in 2007. I first calculate the foreclosure timeline for each individual loan in ABSNet and then average across all loans in each state to obtain a state-level measure.¹⁸ As a comparison, I also use 2007 foreclosure timelines calculated by RealtyTrac.¹⁹ However, the RealtyTrac data have less coverage, with only 36 states covered in 2007. Table 4 presents the average foreclosure timeline for each state using both measures and an indicator for whether the state requires judicial foreclosures.²⁰ Figure 2 presents the same data in a map for easier visualization. It is clear to see that judicial states had longer timelines, with some judicial states having a timeline over one year, and that the majority of judicial states are in the Northeast and Midwest.

Lastly, I supplement the individual loan-level data with zip code data on home prices, rents, unemployment rates, and income. I get my home price index and housing market turnover rates from Zillow.²¹ For rents, I use the 2000 Census zip code-level rent-to-income ratio. I get employment data from the Bureau of Labor Statistics Local Area Unemployment Statistics and income from the IRS.

Table 5 presents summary statistics for the ABSNet and supplemental data. Panel A presents loan-level counts and variable means. There is a smaller share of short sales to foreclosures compared with DataQuick transaction data. This difference may be due to the fact that ABSNet only has PLS loans, which could have been more restrictive of short sales, while DataQuick contains transactions for all loan types. Loan characteristics are significantly different between these types of transacted

¹⁸There is too much idiosyncratic noise at the individual loan level, so a state-level average will be a more reliable measure. Also, I calculate foreclosure timelines at the state level because judicial foreclosure laws are the same within a state, and these laws shape foreclosure timelines.

¹⁹RealtyTrac foreclosure timeline data come from <http://www.baltimoresun.com/news/data/bal-average-length-of-foreclosure-by-state-by-number-of-days-20140924-htmllstory.html>.

²⁰State judicial foreclosure law classification comes from Gerardi, Lambie-Hanson, and Willen (2013).

²¹The data were acquired from Zillow.com/data on January 2016. Aggregated data on this page are made freely available by Zillow for noncommercial use.

homes. Panel B presents summary statistics on both state-level and zip code-level variables. The mean 2007 ABSNet foreclosure timeline measure is 0.58 years (7 months) with a 0.29-year standard deviation, while both the mean and the standard deviation for the 2009 measure is longer at 0.71 years (9 months) and 0.37 years, respectively.

4 Benefits of Short Sales over Foreclosures

4.1 Benefit for Home Prices

4.1.1 Empirical Setup

Since foreclosures and short sales are two different ways to deal with the same problem of delinquency, it is important to understand how they may impact the selling price of a home differently. As shown by previous research, selling a home in foreclosure leads to a discount on the transaction price (Campbell, Giglio, Pathak (2011) and Clauretje and Daneshvary (2009)). One reason may be because foreclosed homes tend to be in worse condition, especially since the previous owners have no incentive to maintain them if they know that they will lose their homes, and lenders lack the ability to properly maintain them. A desire by banks to sell the home faster in a fire sale may also play a role in lowering the selling price. However, Harding, Rosenblatt, and Yao (2012) find this discount is not the result of fire sales.

Because short sales transact differently from foreclosure sales, they should have a different discount. Homeowners who wish to do a short sale must have the lender approve their selling price, so they have an incentive to properly maintain their homes to achieve a high enough selling price that will be approved.²² A lack of maintenance may lower the price too much to be accepted for a short sale by the lender. However, a price discount may still exist for short sales because of the urgency to sell. Short sales also take less time to process than foreclosures and are lower risk for the potential buyer, since the seller will be more knowledgeable about the home, and the buyer can be more informed about what he is buying.

To test for the foreclosure discount versus the short sale discount, I run a hedonic home price

²²The DataQuick sample is not restricted to only PLS loans. Thus, the agent approving the short sale is not restricted to just the loan servicer, so I use the term lender to refer to any agent that makes the short sale approval decision. As a result, the recovery value on the mortgage can influence the success of a short sale as detailed in Table 1.

regression with indicator variables for foreclosure sales or short sales. The equation I estimate for measuring the foreclosure and short sale discount is:

$$\ln P_{ict} = \alpha_{ct} + \beta X_i + \lambda_f * foreclosure_{it} + \lambda_s * shortsale_{it} + \epsilon_{ict}, \quad (1)$$

where $\ln P_{ict}$ is the log selling price of home i in census tract c and half year t ; X_i includes a set of house characteristics; $foreclosure_{it}$ and $shortsale_{it}$ are dummies indicating if home i sold as a foreclosure or a short sale at time t ; α_{ct} are census tract by half-year fixed effects; and ϵ_{ict} are the error terms.²³ I also include month dummies to control for seasonality effects in the housing market. Standard errors are clustered at the county level.

A naive OLS estimate of equation (1) will produce biased results due to omitted variable bias. I can only include controls for observable home characteristics, and any unobserved characteristics influencing both home prices and foreclosures or short sales will bias my estimate. Most notably, home quality is a factor that I cannot observe and is correlated with both selection into short sale and the transaction price. Lambie-Hanson (2015) showed that, although home conditions deteriorate the most after a foreclosure when a home is bank owned, borrowers do begin to neglect home maintenance when they first become delinquent. Variation in home quality at first delinquency causes bias by affecting both the likelihood of a short sale and the transaction price. However, variation in home quality after foreclosure because of bank negligence is exactly the variation I want to capture in the difference between the foreclosure and short sale discount.

4.1.2 Addressing Omitted Home Quality with the Intent to Sell

One way to try to control for initial differences in home quality is to condition on the intent to sell by using home listings.²⁴ Homeowners who list their homes for sale have incentives to keep it well maintained to achieve the highest possible price. A higher selling price will increase the likelihood that a short sale is approved, so delinquent borrowers who intend to do a short sale will have homes in better condition compared with delinquent borrowers who don't attempt a short sale before foreclosure. Merging the listing data with the transaction data allows me to observe when a home was listed prior to a transaction. This merged data set includes all homes that ever

²³I use half-year time intervals because later on I will be measuring nearby transaction counts in six-month windows.

²⁴I define *initial home quality* as quality at first delinquency.

had a listing so I can observe listings for homes in foreclosure that never sold.

For a home that went through the foreclosure process and later transacted either in a foreclosure auction or as an REO property, I classify it as prelisted if I observe a listing any time in the two years prior to the completion of the foreclosure.²⁵ I do not need to observe if a short sale had a listing because every short sale must be listed to sell. I can then compute the foreclosure discount separately for nonprelisted and prelisted foreclosures and compare it with the short sale discount.

Table 6 shows the results of splitting foreclosures into prelisted and nonprelisted. First, I estimate equation (1) without separating the two different types of foreclosures using both the larger transactions-only sample and the smaller merged transaction-listing sample to see if using just the smaller merged sample generates any bias. Column (1) reports the estimate from the larger transactions-only sample, while column (2) uses the smaller merged sample. Both estimates are similar and suggest that foreclosures sell at 11.2% lower prices than short sales, so there are no sample bias concerns when using the merged data set.

I then estimate the discount difference between prelisted foreclosures and nonprelisted foreclosures in two different ways. In column (3), I first estimate equation (1) after excluding all nonprelisted foreclosures. The results show that prelisted foreclosures sell at slightly lower discounts compared with all foreclosures — a 23.8% discount versus a 26.0% discount as reported in column (2). I then use the entire merged sample again but include an additional indicator variable for if a home sold as a prelisted foreclosure. The estimates reported in column (4) again show that prelisted foreclosures have a 2.1% smaller discount. However, in comparison with the short sale discount, the foreclosure discount is still 9.6% higher even just for prelisted foreclosures, which suggests that initial home quality alone cannot explain the difference in the discounts.

4.1.3 Addressing Omitted Home Quality with Instrumental Variables

An additional way to account for omitted home quality is to instrument for the probability of a successful short sale. When estimating equation (1), I estimate how much lower the transaction price is selling a home as a foreclosure or a short sale relative to selling it as a normal sale. To be

²⁵Since foreclosure timelines can be well over a year in some states, the homeowner may have already been delinquent on his mortgage and looking to do a short sale up to two years prior to the completion of the foreclosure. I also estimated everything using a 1.5-year window to classify prelisted foreclosures instead and had similar results everywhere.

able to instrument for the success of a short sale, I now modify my empirical setup by focusing only on the sample of prelisted foreclosures and short sales and estimate the discount of a foreclosure sale relative to a short sale, which I call the relative foreclosure discount. In estimating this equation, I will only have one indicator variable — for a foreclosure sale — for which I can instrument.

The instrument I use is the imputed percentage of the mortgage outstanding at the time of listing — defined as the outstanding loan balance divided by the original loan amount.²⁶ This percentage is imputed because I do not observe the actual balance at listing. The calculation of this percentage is based on the future value formula for a 30-year fixed rate mortgage with monthly payments. For each home i with a mortgage interest rate r_{t_1} originating at time t_1 and listed at time t_2 , I calculate the imputed percentage outstanding as:

$$outstanding\%_{i,t_1,t_2} = \frac{(1 + r_{t_1})^{360} - (1 + r_{t_1})^{(t_2-t_1)}}{(1 + r_{t_1})^{360} - 1}. \quad (2)$$

In the transaction data, I can find the origination date t_1 from the previous first-lien mortgage taken out on a home that ended in either foreclosure or short sale.²⁷ I am able to use the entire DataQuick transaction history dating back to 1988 to look up the loan record because I no longer need short sale flags. I obtain weekly mortgage rates from the Freddie Mac Primary Mortgage Market Survey.²⁸ I also discard homes that had a loan originated less than six months before the listing, since it's not plausible that a borrower becomes delinquent right after obtaining a new loan, and loans originating before 2004, since older loans had more equity and were less likely to default.

In order for the percentage of the mortgage outstanding to be a good instrument, it must have a strong first stage and satisfy the exclusion restriction. I claim that the percentage of the loan outstanding significantly impacts the probability of a listed home failing the short sale and becoming a foreclosure because banks may be more weary of accepting a short sale if the losses are higher. By including home characteristics and having census-tract by half-year fixed effects in my regression, I can control for the market value of the home so the losses on the mortgage will

²⁶A similar instrument has been used by others. Bernstein (2016) uses the percentage of mortgage paid instead of outstanding to instrument for the probability of negative home equity. Guren (2018) uses the log of the ratio of home price, instead of loan value, at listing and the previous transaction as an instrument for the seller's listing price markup.

²⁷The previous mortgage could either be a purchase loan or a refinance. In the case of a refinanced loan, I need to distinguish it from a second mortgage. I classify a loan as a refinance if it is at least two-thirds the value of the previous first-lien mortgage.

²⁸Obtained from http://www.freddiemac.com/pmms/pmms_archives.html.

only be driven by the unpaid balance. Column (1) of Table 7 reports the first stage results. I find that loans with higher balances are more likely to end in a foreclosure with strong statistical significance, which provides evidence of a strong instrument.

The exclusion restriction is satisfied if the instrument does not impact home prices except through the probability of a short sale. Since I'm assuming the same interest rate for every origination week and constant payments from origination to listing, variation in the percentage of the mortgage outstanding only comes from the time when the loan was made and the length of time between origination and listing, which can be thought of as the age of the loan at listing. One may argue that the exclusion restriction does not hold because borrowers who obtained a loan later during the housing boom may be borrowers of lower quality because of looser credit standards. These borrowers may have defaulted more and may have been more careless about maintaining their homes. However, Palmer (2015) showed that home price declines, and not changes to borrower characteristics related to credit expansion, can explain the majority of the difference in default rates among cohorts. Since differences in borrower characteristics were not primarily responsible for the higher default rates, I also assume that it was less likely that they were linked to lower quality homes.

To further address the problem of borrower quality varying over time due to looser credit standards, I focus my analysis on only mortgages that originated between the fourth quarter of 2007 and the end of 2011. When the housing market collapsed and banks suffered big losses, mortgage lending tightened. Furthermore, the private-label securitization market dried up in the fourth quarter of 2007. As a result, it became much more difficult for borrowers of lower quality, such as those with insufficient income, to obtain mortgages. Therefore, it is less likely for the origination year to influence home prices through borrower quality during this period.

Columns (2) and (3) present the results of estimating the relative foreclosure discount using IV. Column (2) first reports the OLS estimate of the relative foreclosure discount using the new sample. I obtain an estimate of 9.2%, which is consistent with the difference in previous estimates of the foreclosure and short sale discount for prelisted foreclosures from Table 6. When I implement the IV regression in column (3), I find a slightly larger relative foreclosure discount of 10.4%. Column (4) reports the estimate using the restricted sample of loans that were originated between the fourth quarter of 2007 and the end of 2011 to control for borrower quality. I again find that the

relative foreclosure discount is 9.2%. Thus, the use of an IV provides further evidence that omitted variable bias is not causing the difference in the transaction discounts between homes selling after foreclosures and homes selling via short sales.

4.2 Benefits for the Local Housing Market

While short sales and foreclosure sales deflate the selling price of the home itself compared with a nondistress sale, their negative price impacts may also extend to surrounding homes. And just as they have different discounts, they should have different externalities. There has been overwhelming evidence of negative price externalities associated with foreclosures, but less is known about the externalities from short sales.

To test how short sales affect the selling price of neighboring homes, I run a similar difference-in-difference regression as employed by Campbell, Giglio, and Pathak (2011) and Anenberg and Kung (2014). I use the number of foreclosure sales and short sales that occurred around each home to estimate the externalities. I obtain counts at both a close distance (0.10 miles) and a far distance (0.25 miles) in each six-month period within a three-year window around the transaction date for each home — both one and a half years before and after. Counts at the far distance serve as a control for preexisting local neighborhood-level economic shocks that may be affecting both prices and the number of distress sales because these shocks should not have differential effects for the close distance versus the far distance.

Like previous work, I find that foreclosure sale and short sale counts are extremely right skewed. To adjust for this, I employ the same method as Anenberg and Kung (2014) and take the log of 1 plus the counts. Then I run the following regression with lags and leads up to one and half years around each sale:

$$\ln P_{igt} = \alpha_{gt} + \beta X_i + \lambda Y_{it} + \sum_{k \in \{-1.5, 1.5\}} (\gamma_{f,t-k}^c \text{foreclosurecount}_{i,t-k}^c + \gamma_{f,t-k}^f \text{foreclosurecount}_{i,t-k}^f + \gamma_{s,t-k}^c \text{shortsalecount}_{i,t-k}^c + \gamma_{s,t-k}^f \text{shortsalecount}_{i,t-k}^f) + \epsilon_{igt}, \quad (3)$$

where $\text{foreclosurecount}_{i,t-k}^c$ and $\text{shortsalecount}_{i,t-k}^c$ are foreclosure sale and short sale counts within a close distance of home i measured k periods from time t ; $\text{foreclosurecount}_{i,t-k}^f$ and $\text{shortsalecount}_{i,t-k}^f$ are foreclosure sale and short sale counts within a far distance; and Y_{it} includes

indicators for if the transaction of home i at time t is a short sale or foreclosure sale and indicators for if home i had 0 short sales or foreclosure sales from $t - 1.5$ to $t + 1.5$ within a close distance. I use sales from July 2005 to June 2012 since I have one and a half years of lags and leads. Standard errors are clustered at the county level.

After estimating the coefficient for the close counts for each of these six periods, I then normalize the coefficient in the earliest period to 0 and index all subsequent coefficients to it.²⁹ The indexed coefficients on the close counts represent the externality effect. Figure 3 shows the plots of the indexed $\gamma_{f,t-k}^c$ and $\gamma_{s,t-k}^c$ for the different values of k after estimating equation (3). The solid lines are the estimates themselves and the dashed lines are 95% confidence intervals. The plots can be interpreted as the impact of one additional close foreclosure sale or short sale relative to one additional far sale. We can see strong evidence of different externalities associated with each type of sale. Each foreclosure sale decreases nearby home prices by up to 0.8% right after the foreclosure sale itself, and this negative foreclosure externality still exists one and a half years after the foreclosure sale itself. On the other hand, the short sale externality is non-existent.

While I find evidence of a foreclosure externality, my estimates of the magnitude or duration of the externality differ from previous research. In their study of four different MSAs between 2007 to 2009, Anenberg and Kung (2014) find that each foreclosure sale decreases the price of nearby homes by 0.6%, which is similar to my estimate of 0.8%. However, they showed this externality price effect disappears six months after the foreclosure sale, while I find that the externality still exists one and a half years after the foreclosure sale. Using a sample of sales in the state of Massachusetts dating back to 1988, Campbell, Giglio, and Pathak (2011) also find evidence of foreclosure externalities lasting more than a year, but they estimate the impact of each foreclosure sale to be 2%, which is much higher than my estimate. The samples used in these studies were either limited by time or location, so it may be difficult to generalize these results. The benefit of my study is that I use data with wider geographical coverage during the entire housing crisis, so my estimates are more nationally representative of what happened during the housing crash.

Given the focus of extant research on the existence of the foreclosure externality, I use the foreclosure externality itself as a benchmark and reformulate equation (3) to instead focus on the *relative* externalities of foreclosure sales. That is, I estimate the externality of a foreclosure sale

²⁹Campbell, Giglio, and Pathak (2011) only run this regression for counts a year before and a year after so they just take the difference between the past and future coefficient.

relative to the externality of a short sale to see how much better short sales are than foreclosures for the local housing market. I run the following regression to test for the relative externality of foreclosure sales:

$$\ln P_{igt} = \alpha_{gt} + \beta X_i + \lambda Y_{it} + \sum_{k \in \{-1.5, 1.5\}} (\gamma_{f,t-k}^c \text{foreclosurecount}_{i,t-k}^c + \gamma_{f,t-k}^f \text{foreclosurecount}_{i,t-k}^f + \gamma_{d,t-k}^c \text{distresscount}_{i,t-k}^c + \gamma_{d,t-k}^f \text{distresscount}_{i,t-k}^f) + \epsilon_{igt}, \quad (4)$$

where $\text{distresscount}_{i,t-k}^c$ and $\text{distresscount}_{i,t-k}^f$, which are the sum of close and far short sale and foreclosure sale counts, replace $\text{shortsalecount}_{i,t-k}^c$ and $\text{shortsalecount}_{i,t-k}^f$ from equation (2). $\gamma_{f,t-k}^c$ now represents the externality of a close foreclosure sale relative to that of a close short sale. Again, standard errors are clustered at the county level, and I index the coefficient estimates by the initial period's estimate, which is normalized to 0.

Figure 4 plots $\gamma_{f,t-k}^c$ over k . The results here in effect represent the difference between the two lines from Figure 3. The relative externality for foreclosure sales starts to become negative and statistically different from 0 for homes that sell less than half a year before a distress sale. This negative relative externality grows as the distress sale occurs later relative to the date of a home sale. A year after a distress sale has occurred, home prices are about 1 percentage point lower for homes near a previous foreclosure sale than those near a previous short sale. These results show that short sales are better than foreclosures for the housing market because they don't lower the price of nearby homes as much as foreclosures do.

Again, I have to contend with omitted variable bias because initial home quality could be dictating the success of a short sale and influencing nearby home prices. I separate out prelisted foreclosures from nonprelisted foreclosures to condition for home quality. Before estimating the foreclosure externality separately for nonprelisted and prelisted foreclosures, I first estimate equation (4) for all foreclosures using the smaller merged data set. The result in Figure 5 shows that the relative externality is weaker in this new sample, but foreclosures still do have a larger negative externality relative to short sales.

Figure 6 plots coefficient estimates of $\gamma_{f,t-k}^c$ over k for each type of foreclosure separately. We can see that the relative externality for foreclosed properties that were prelisted is not significantly different from those that were not prelisted, suggesting that omitted home quality is not driving

the relative foreclosure externality. Thus, since I find that the type of foreclosure does not influence the externality, I use my original transactions-only data set to run further robustness checks. The advantage of using the transactions-only data set is that it contains transactions going back to 2004, which allows me to use transactions during the entire housing crash in my regressions. These additional robustness checks are shown in the Appendix.

4.3 Discussion

While I show that short sales do not lower home prices as much as foreclosures, it is also important to understand why. What differences between the two types of transactions cause foreclosures to sell at a lower discount and decrease nearby prices more? While I do not test for the different factors that cause the price differences, I speculate on a few reasons for this difference. Further research is needed to break out the individual channels.

The most obvious cause is differences in home quality. I do control for variation in initial home quality that may cause endogenous selection into short sale. However, home conditions continue to deteriorate even after the foreclosure is complete due to negligence by the banks (Lambie-Hanson (2015)) so there can still exist differences in home quality between short sales and foreclosure sales. Quality affects the transaction price simply because quality itself is priced but also because a lower quality home will require a cash-only transaction if the conditions are too poor to qualify the home for a loan, which further reduces the transaction price by decreasing the number of potential buyers.

Second, the two types of transactions convey different amounts of information for the potential buyer. With a short sale, the buyer is able to view the home and consult real estate agents with any questions that may arise. When someone is buying a foreclosed home, the transaction may not be as transparent and bidders may not even get to view the home before buying. Also, banks looking to liquidate homes may know less about the home and may spend less time trying to answer all of the potential buyer's questions.

Lastly, there is a difference in the urgency to sell. Bank are more intent on liquidating the home after foreclosure than when deciding to approve a short sale. They may only approve of a short sale if the price is high enough because they know they can always liquidate the home later via foreclosure, and the prospect of selling later may yield a higher price if the housing market rebounds. Prior to the home becoming REO, maintenance costs can also be charged to the borrower of the

loan. Once the home has become REO, banks may be in a greater rush to sell the home, especially if maintenance costs are high. Shleifer and Vishny (1992) showed that a fire sale occurs when an asset is forced to be sold and the potential buyers are unable to buy the asset, leading to the asset selling at lower prices to parties who value the asset less. Both types of transactions are occurring in the same economic environment where homeowners are limited in their ability to buy homes. However, foreclosure sales are more like fire sales because the greater urgency to sell makes them forced sales, which lowers the price.³⁰

The causes of the foreclosure externality have been well documented to be caused by either a supply channel or a disamenity channel. Anenberg and Kung (2014) and Hartley (2014) showed that foreclosures decrease nearby home prices by increasing the supply of homes, while Fisher, Lambie-Hanson, and Willen (2015) and Gerardi et al. (2015) showed that foreclosure externalities are the result of disamenities or poor conditions. Given that both a foreclosure and short sale increase the supply of homes on the market, the supply effect should lead to similar externalities for the two transactions. However I find evidence of different externalities for the two, which suggests that the supply channel does not explain the larger foreclosure externality.

Instead, the disamenity channel can explain the relative foreclosure externality due to the timing of the externality. My results show that the externality differences begin shortly before the distress sale itself, which is the time when the home is bank owned, suggesting that the lack of maintenance during REO is causing a spillover. The growth of the negative externality after the distress sale could reflect a delay in the time it took to clean up the disamenities that resulted from the foreclosure. The persistence of the externality could result from the use of the foreclosure sales as comparables for other homes on the market. Since short sales transact at higher prices than foreclosure sales, they can lead to a higher “reference” price for the neighborhood.

³⁰Pulvino (1998) has also shown that fire sales decrease prices by looking at the sale of commercial aircrafts by distressed airlines.

5 Explaining Why Short Sales Weren't More Prevalent

5.1 Empirical Setup and Results

Because short sales were better for home prices than foreclosures, it is surprising that there were fewer short sales than foreclosures during the housing crash. However, because these home price benefits did not apply directly to the agents who make the short sale decision, short sales were not optimal for them. Instead, foreclosures may have provided more benefits, and as foreclosure timelines increased, the benefits may also increase. For borrowers, the option to go down the foreclosure path provides them with free housing during the entire foreclosure process, which makes foreclosure a more attractive option, especially during times of financial distress for the borrower. If a borrower could not afford to make mortgage payments, he may also have trouble moving out and renting a home, so a faster exit out of the home via a short sale would not be preferred. When foreclosure timelines are longer, the borrower is able to capitalize on even more free rent when selecting foreclosure, so the decision to do a foreclosure will be even more attractive.

While the borrower is the one who initiates the short sale, he must find a buyer who submits an offer that the servicer of his loan will approve. Even if all borrowers wanted to do short sales, servicers may still decline some of them. Servicers have more time to collect servicing fees if they foreclose on a home, but they also want to avoid waiting to recoup advances that have already been made. If servicers do not have enough cash on hand, they would have to finance the cost of their advances, which makes the recovery of advances more urgent, since servicers are borrowing to make what is essentially an interest-free loan. A longer foreclosure timeline can increase the servicing fees they can collect, but it will also delay the recovery of these advances. Thus, the impact of longer foreclosure timelines on the servicer's decision is more ambiguous.

To test for the impact of foreclosure timelines on the unpopularity of short sales, I estimate how differences in state-level foreclosure timelines affected the probability that a delinquent loan will end in a short sale. In the data, I can only observe the outcome for the home — whether it was foreclosed on or sold as a short sale. If I see a foreclosure, I do not know if the borrower decided to allow the foreclosure or if the servicer declined the short sale. When I test for impact of foreclosure timelines on the probability of a short sale, I control for factors that affect how both the borrower and servicer respond to different foreclosure timelines. There is also the possibility that, due to

poor housing market conditions, a home listed as a short sale never receives an offer. The servicer will not wait forever for an offer to come along and will eventually have to foreclose on the home. Thus, I control for housing market conditions as well.

I test for the impact of foreclosure timelines on the probability that a delinquent loan will end in a short sale after including controls for factors that influence both the borrower and servicer decision as well as loan characteristics and general zip-code level economic controls. I use a linear probability model (LPM) to estimate:

$$\begin{aligned} \text{shortsale}_{i,z,s,t_1,t_2} = & \alpha + \beta_1 \text{foreclosures}_{i,z,s,t_1,t_2} + \theta X_{i,z,s,t_1,t_2} \\ & + \eta_{t_1} + \eta_{t_2} + \eta_{\text{servicer}} + \epsilon_{ict}, \end{aligned} \tag{5}$$

where $\text{shortsale}_{i,c,s,t_1,t_2}$ is an indicator for a delinquent loan i in zip code z and state s with an origination year t_1 that became 90-days delinquent in year t_2 and ended in a short sale; $\text{foreclosures}_{i,z,s,t_1,t_2}$ is the 2007 foreclosure timeline measured in years for state s ; X_{i,z,s,t_1,t_2} are controls that include loan characteristics and zip code-level economic and housing market conditions; and η 's are fixed effects for year of loan origination, year of distress, and loan servicer.³¹ Standard errors are clustered at the zip code level.

Estimates of equation (5) could be plagued by endogeneity between short sales and foreclosure timelines. Reverse causality exists if low short sale probabilities increased foreclosure counts, and this increase led to longer foreclosure timelines. I aim to get around reverse causality by measuring foreclosure timelines in 2007 while using a sample of loans that became delinquent between 2008 and 2013 to run my analysis. Loans that became delinquent later should not affect the 2007 foreclosure timeline measure. However, there may still be unobserved regional-level variation arising from omitted variables that could be driving both foreclosure timelines and the probability of a short sale. Since my foreclosure timeline measure varies at the state level, I am unable to include any

³¹One variable that I cannot control for with the ABSNet data is whether a mortgage has a junior lien. Lee, Mayer, and Tracy (2012) have documented that up to 45% of home purchases during the housing boom in the hot markets had a second lien, and that this number was higher for owner occupant buyers. However, with my merged transaction and listing data, I can observe which loans ended in foreclosure or short sale with a junior lien. Summary statistics with this data show that 36.6% of loans without a junior lien and 34.9% of loans with a junior lien ended in a short sale over a foreclosure. Thus, preliminary evidence suggests that the presence of a junior lien does not appear to be correlated with short sales. I am unable to conduct a more thorough analysis with the merged transaction and listing data because it lacks data on borrower and loan characteristics, so further research is required to better understand the impact of junior liens.

regional-level fixed effects in my regression to help control for the omitted variables.

To deal with endogeneity, I rely on an instrumental variables approach similar to the one used by Mian, Sufi, and Trebbi (2015). For each state, I know whether the law requires a judicial foreclosure or not. These judicial foreclosure laws serve as a good instrument because they are directly related to the foreclosure timeline as highlighted by Pence (2006), and their historical adaptations were exogenous to economic factors according to Ghent (2013).

Table 8 reports the results from both the first stage regression and the 2SLS IV regression. Columns (1) and (2) report the first stage estimates. The results show that states that allow judicial foreclosures have foreclosure timelines that are 0.63 years longer, regardless of whether servicer fixed effects are included or not. Columns (3) and (4) report the 2SLS IV regression. While it is plausible that some servicers may be more short sale friendly, the results do not change from column (3) to column (4) when I include servicer fixed effects to control for differences across servicers. The coefficient estimate of -4.2% implies that increasing the 2007 foreclosure timeline by one standard deviation decreases the probability that a delinquent loan will end in a short sale by about 1.2%. Applying this coefficient estimate to the 2009 ABSNet foreclosure timelines, I find that short sales decrease by 1.5%. Thus, a standard deviation increase in the foreclosure timeline can explain a 0.35-0.45 standard deviation decrease in the state-level short sale share of distressed sales. When I use the RealtyTrac measurement of the 2007 foreclosure timeline in column (5), I obtain a larger estimate in magnitude, which may be explained by the RealtyTrac measure having less coverage and being shorter on average.

5.2 Borrower and Servicer Analysis

5.2.1 Borrower Differences

One caveat about the ABSNet data is that since they consist only of PLS mortgages, there is a larger proportion of subprime loans, which may be driving the results. Subprime borrowers are borrowers of lower quality who tend to have lower credit scores and incomes, so I would expect them to prefer foreclosures even more because the benefit of free housing from foreclosure will make a bigger difference for them than the benefits from short sales. Thus, it is useful to analyze how heterogeneity across borrower quality affects the impact of foreclosure timelines on the probability

of a short sale.

While including FICO scores allows me to control for borrower quality, it alone does not allow me to distinguish how borrowers of different quality may respond to foreclosure timelines. As a way of testing for the heterogeneous impact of borrower quality, I break out the borrowers in my sample into subprime, Alt-A, and prime borrowers as defined by the loan issuer. Within each of these samples, I continue to control for FICO scores.

Table 9 reports estimation results for each type of borrower. I find that foreclosure timelines have the largest impact for the riskiest borrowers as shown in column (1). The coefficient estimate of -5.0% is larger in magnitude than the mean estimate for the whole sample of -4.2%. As the borrower quality improves when moving from column (1) to column (3), the impact of foreclosure timelines decreases. For prime borrowers, the foreclosure timeline does not have a statistically significant impact on short sales. Thus, I do find evidence that borrowers of lower quality are primarily responsible for the impact of foreclosure timelines on short sales because the benefits from foreclosures are even more valuable than the benefits from short sales for these borrowers.

5.2.2 Servicer Differences

On a similar note, I also expect that heterogeneity across servicers can affect the impact of foreclosure timelines on short sales. There is a wide spectrum of mortgage servicing companies that service PLS mortgages, ranging from large bank holding companies to smaller financial institutions that specialize in mortgage servicing. Thus, the impact of foreclosure timelines on short sales can vary greatly for different types of servicers depending on the cost and benefit trade-off between servicing fees and advances. I would expect companies that focus primarily on servicing to be the most sensitive to different foreclosure timelines.

The use of servicer fixed effects in my initial analysis helps me control for servicer differences. When comparing column (3) to column (4) in Table 8, I show that adding servicer fixed effects did not affect the foreclosure timeline coefficient estimate at all. To better understand the differences among servicers, I group the servicers in my sample in two ways. First, I group servicers based on how many loans they service in my sample into three size groups. Large servicers are those that service over 100,000 loans in my sample, medium servicers are those that service over 20,000, and small servicers make up the rest. Then I group servicers as bank holding companies (BHCs) and

as nonbank holding companies.

I present the estimates from the different groups of servicers in Table 10. Columns (1) to (3) show estimates of the foreclosure timeline coefficient for the three size groups of servicers. The coefficient estimate is smaller in magnitude for large and small servicers compared with the mean effect from Table 8 — -2.3% and -2.7%, respectively, versus -4.2%. On the other hand, the estimate for the medium group is much larger in magnitude at -7.4%. The medium group contains the specialized mortgage servicing companies, so it makes sense that they are the most sensitive to foreclosure timelines. When I only look at the BHCs in column (4), I again get a smaller estimate of -3.7%, which is due to the fact that all of the large servicers are also BHCs.

5.2.3 Testing for Borrower Channel Versus Servicer Channel

The estimates so far have shown that longer foreclosure timelines cause fewer short sales and that this effect varies across different types of borrowers and servicers. However, they do not distinguish if the effect is driven by the borrower or the servicer reacting to different foreclosure timelines. As mentioned before, borrowers like foreclosures because they get free rent, while servicers like foreclosures because it allows them to collect more fees but at the expense of waiting longer to recoup advances. If servicers have already made significant advances, they may actually prefer short sales instead to recoup their advances sooner, especially if they had to start borrowing to finance them.

I first test to see how rents affect a borrower's response to different foreclosure timelines. Since the impact of rent primarily affects the borrower, I argue that the varying impact of foreclosure timelines due to differences in rent works through the borrower channel. The coefficient estimate on rent from the baseline specification is positive, which suggests that higher rents and short sales are correlated. A region with higher rents having more short sales could be due to a stronger housing market. To further investigate the importance of rents, I test how differences in rents affect the impact of foreclosure timelines on short sales by adding an interaction term between foreclosure timeline and rent to the baseline LPM regression.³² The interaction term captures how rents affect short sales through foreclosure timelines. The rent value I use is the rent-to-price ratio from the

³²I have demeaned both foreclosure timeline and rent so that we can interpret either main effect terms when the other is set to 0. All interacted terms in other regressions are demeaned as well.

2000 census. Using a historical rent value can help eliminate some endogeneity between rent and short sales.

The results of estimating the impact of rents are reported in column (1) of Table 11. The interaction term is negative and significant, which implies that longer foreclosures lead to even fewer short sales in zip codes where rents are higher. At the mean rent level, a one standard deviation increase in the 2007 foreclosure timeline decreases the probability of a short sale by 1.0%. Increasing rent by one standard deviation increases this probability to 1.7%. Thus, I find that borrowers are responding to longer foreclosure timelines by choosing foreclosures more often to maximize the amount of free housing they receive.

Next, I test how servicers respond to varying foreclosure timelines by interacting foreclosure timelines with the loan interest rate to see how sensitive servicers are to advances. While servicers are motivated by both fees and advances, my analysis only tests for the impact of advances because I do not have data on fees. Since advances are equal to the borrower's missed payments, they can be calculated using the loan amount and the loan interest rate. By controlling for loan origination amount, I can then use the loan interest rate as a proxy for advances. After I control for borrower credit score and year of loan origination, I assume that any other variation in the interest rate will be exogenous to short sales. The interaction term captures how advances affect short sales through foreclosure timelines.

The estimates of the impact of advances are reported in column (2) of Table 11. The base term and interaction term are positive and significant, which implies that servicers want to do more short sales when more advances have been made, especially in states with longer foreclosure timelines because they have to wait even longer to recoup fees if they foreclose on homes in those states. At the mean interest rate, a standard deviation increase in the 2007 foreclosure timeline decreases the probability of a short sale by 1.1%. Increasing the loan interest rate by one standard deviation decreases this probability to 0.7%. Thus, I find that servicers are also responding to longer foreclosure timelines by minimizing their costs, but this response actually leads to higher short sale rates.³³

After having found that both the borrower and servicer respond to changes in foreclosure

³³I only show that advances are one factor that affects the servicer's decision and how servicers prefer more short sales when advances are higher. In reality, servicers must take into consideration fees, and their overall response to longer foreclosure timelines may be different.

timelines when testing for each individually, I then test to see how they interact with each other and if one effect dominates the other. Column (3) of Table 11 reports the estimates when I include both interaction terms. The estimate on foreclosure timelines base term and both interaction terms are similar to the estimates in columns (1) and (2), which indicates that both borrowers and lenders are responding to variations in the foreclosure timeline at the same time. Variation in the foreclosure timeline and rent prices drive borrower behavior, while variation in the foreclosure timeline and mortgage interest rates drive servicer behavior.

Columns (4) to (6) repeat the same estimates as columns (1) to (3) but with an IV LPM regression instead of an OLS LPM. The estimates on the foreclosure timeline base term are consistent with the IV estimates in Table 8. The coefficient estimate on the interaction of foreclosure timeline and rent is much smaller in magnitude and not as statistically strong. But it still shows the same relationship, which suggests that rent is still important in explaining why foreclosure timelines cause fewer short sales. The coefficient estimates on the interaction between foreclosure timeline and interest rate are now larger, suggesting that servicers are increasing short sales even more in response to longer foreclosure timelines and higher advance payments.

5.3 Economic Significance

While these coefficient estimates of the impact of foreclosure timelines on short sales may be small in magnitude, their economic impact is not, given the size of the housing market. Increasing short sales by just 5% would have caused 200,000 out of the 4 million completed foreclosures between 2007 to 2011 to be short sales instead. The primary benefit of these additional short sales would be an increase in housing wealth due to higher transaction prices. Given my results showing that foreclosures have roughly a 10% larger discount than short sales and using an average transaction value of \$200,000 for a distressed home sale from my data, a back-of-the-envelope calculation shows that having 5% more short sales would have saved the housing market from a loss of around \$4 billion during 2007-2011.

Furthermore, the secondary benefit of these extra short sales would be a smaller negative externality on the prices of nearby homes, which would have led to even larger savings. For the sample of homes in my data, I find that there are on average approximately four transactions within a 0.1 mile radius around each distress sale up to a year after the distress sale. Based on the estimated

relative foreclosure externality of 1 percentage point, having 5% more short sales would have saved up to an additional \$2.4 billion for the housing market when using \$300,000 as the average transaction value for all homes.³⁴ Thus, there are tremendous social welfare gains to increasing the percentage of short sales, even if only by a few percent, which can be done through shorter foreclosure timelines.

6 Conclusion

Because of the high rates of foreclosures during the housing crash, much research has been done to study the causes and consequences of foreclosures. In addition to undergoing foreclosure, delinquent borrowers also had the option of short sales. A careful study is needed to understand the different economic consequences between short sales and foreclosures. However, the research on short sales is plagued by various endogeneity challenges, such as omitted variable bias and reverse causality, that need to be resolved to establish causal results.

I contribute to the literature by using multiple nationally representative data sets to quantify the benefits of short sales and explain why they weren't more prevalent. Merging the multiple data sets allows me to achieve stronger identification and to address the endogeneity challenges. I find that short sales lead to transaction prices that are 9.2%-10.5% higher than foreclosure sales. Short sales also have smaller negative externalities on the prices of nearby homes by up to 1 percentage point per short sale. Despite all these benefits, short sales were still not utilized as much as foreclosures because longer foreclosure timelines made foreclosures more attractive for delinquent borrowers. I show that a one standard deviation longer foreclosure timeline decreases a state's share of short sales by approximately 0.4 standard deviations.

While these individual results seem small in magnitude, the total economic impact is substantial because of how large the real estate market is. A back-of-the-envelope calculation suggests that having 5% more short sales than foreclosures would have saved up to \$6.4 billion in housing wealth between 2007 and 2011. Thus, the evidence strongly suggests that there needs to be more incentives for short sales. The government and GSEs already began encouraging short sales by offering programs such as HAFAs, starting in 2009, to increase the benefits of short sales for both the

³⁴The average transaction value for all homes regardless of distress is higher than the average transaction value for distressed homes in my data.

borrower and the servicer. However, more could be done such as decreasing foreclosure timelines. If we can continue to increase the incentives for short sales so that they become more popular than foreclosures, future housing downturns may not be as extreme or last as long.

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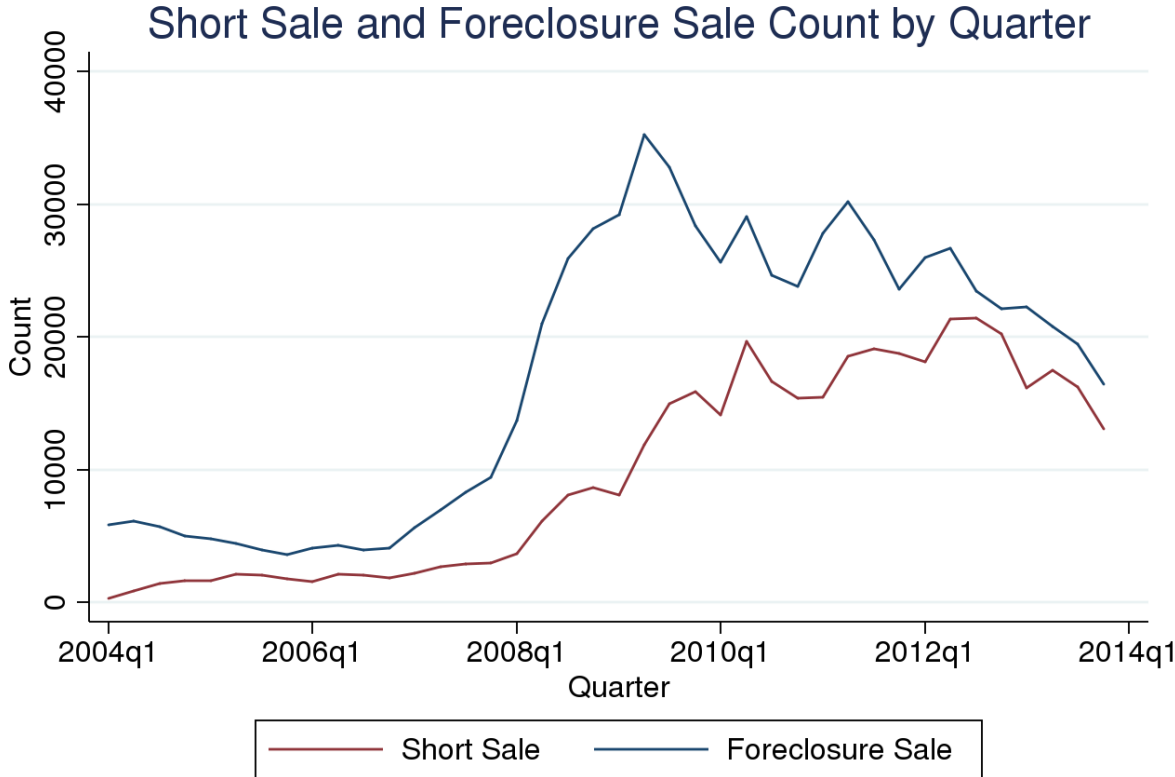
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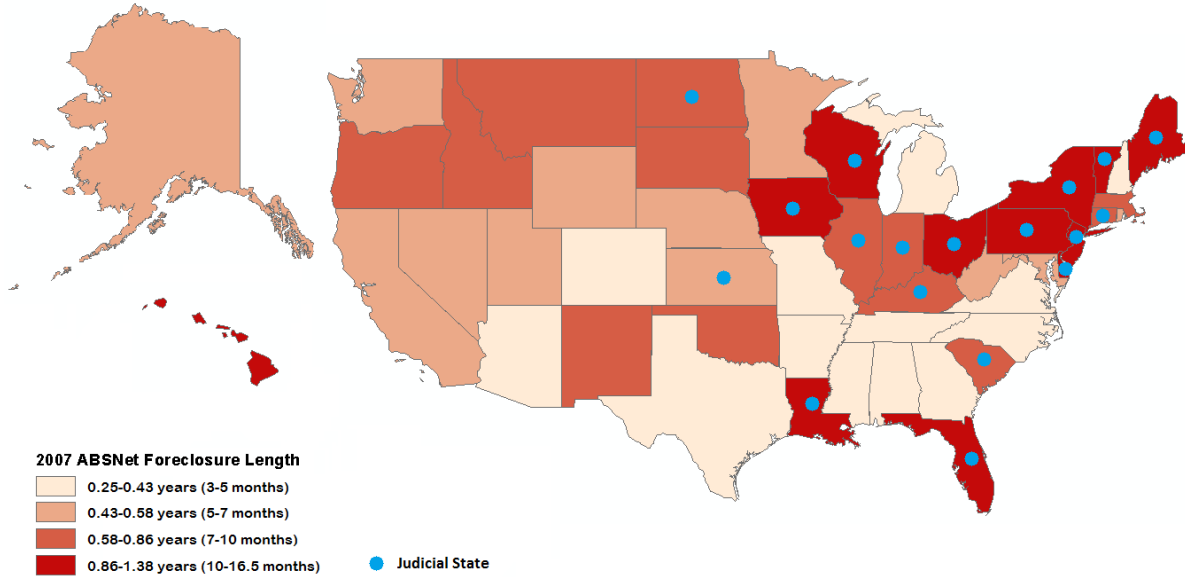
Figure 1 - Foreclosure Sales and Short Sales Over Time



Data from DataQuick 10 MSA Sample

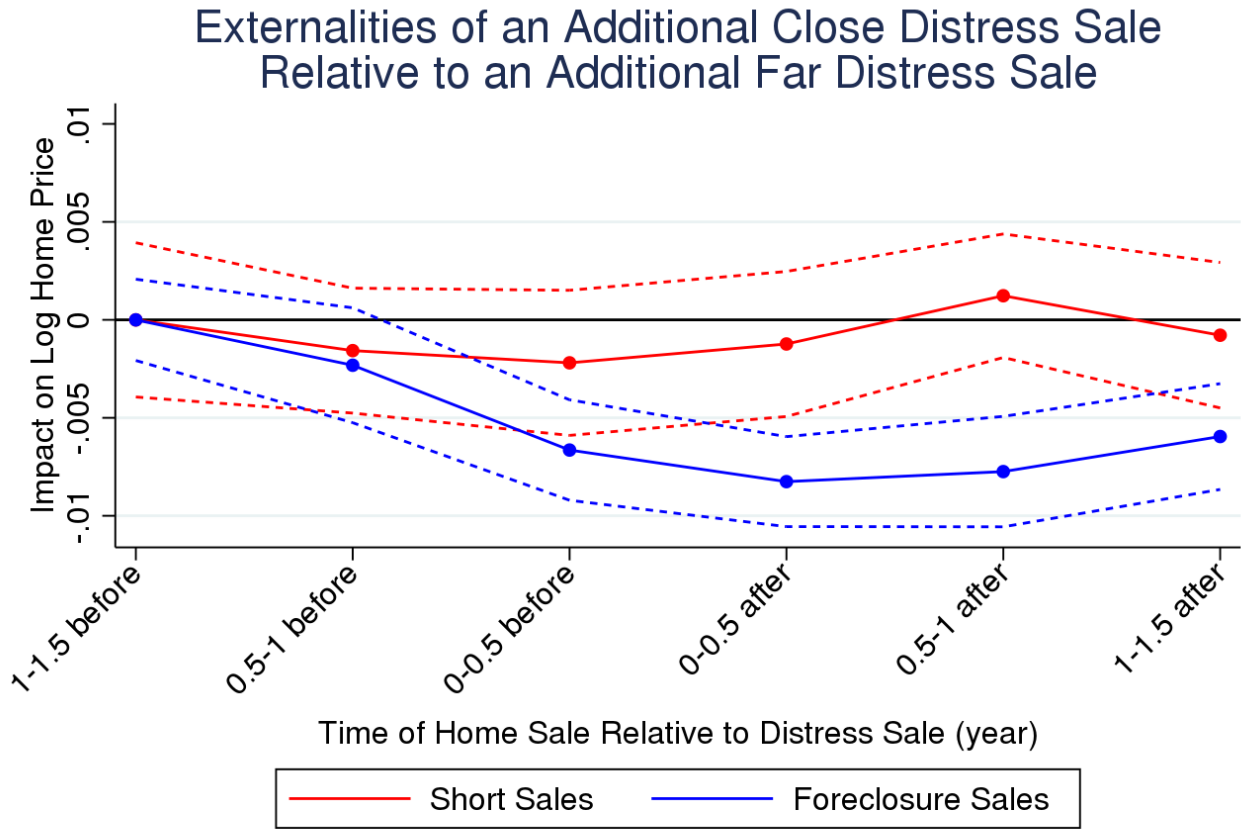
Notes: This figure shows the number of foreclosure sales and short sales in each quarter from 2004 quarter 1 to 2013 quarter 4 for the 10 MSAs in the DataQuick sample.

Figure 2 - Foreclosure Timelines and Judicial Foreclosures Map



Notes: This figure shows a map of the U.S. with each state's foreclosure timeline, as calculated from the ABSNet data, grouped into one of four quartiles. The circle marker designates whether a state allows judicial foreclosures, where the judicial foreclosure law classification comes from Gerardi, Lambie-Hanson, and Willen (2013).

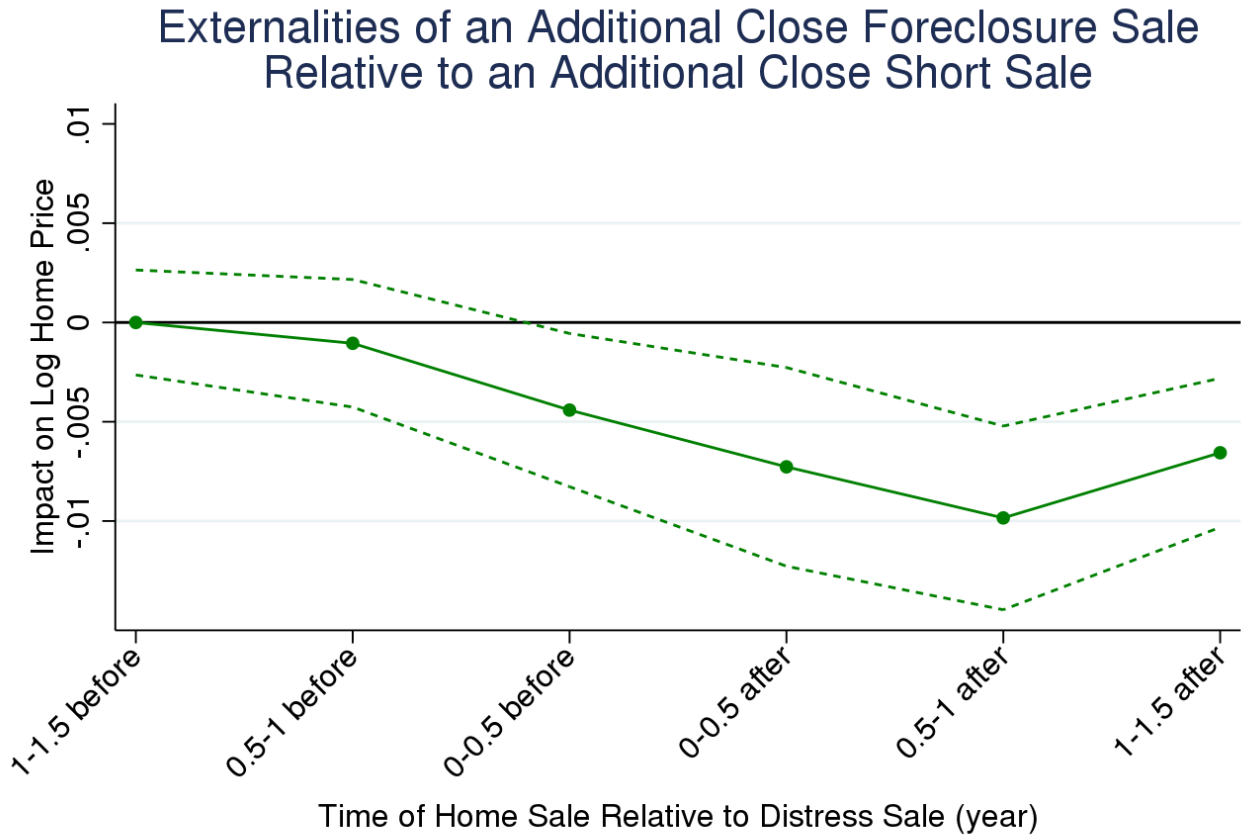
Figure 3 - Price Externalities of Distress Sales



Data from DataQuick; Single family residential home transactions from July 2005 - June 2012

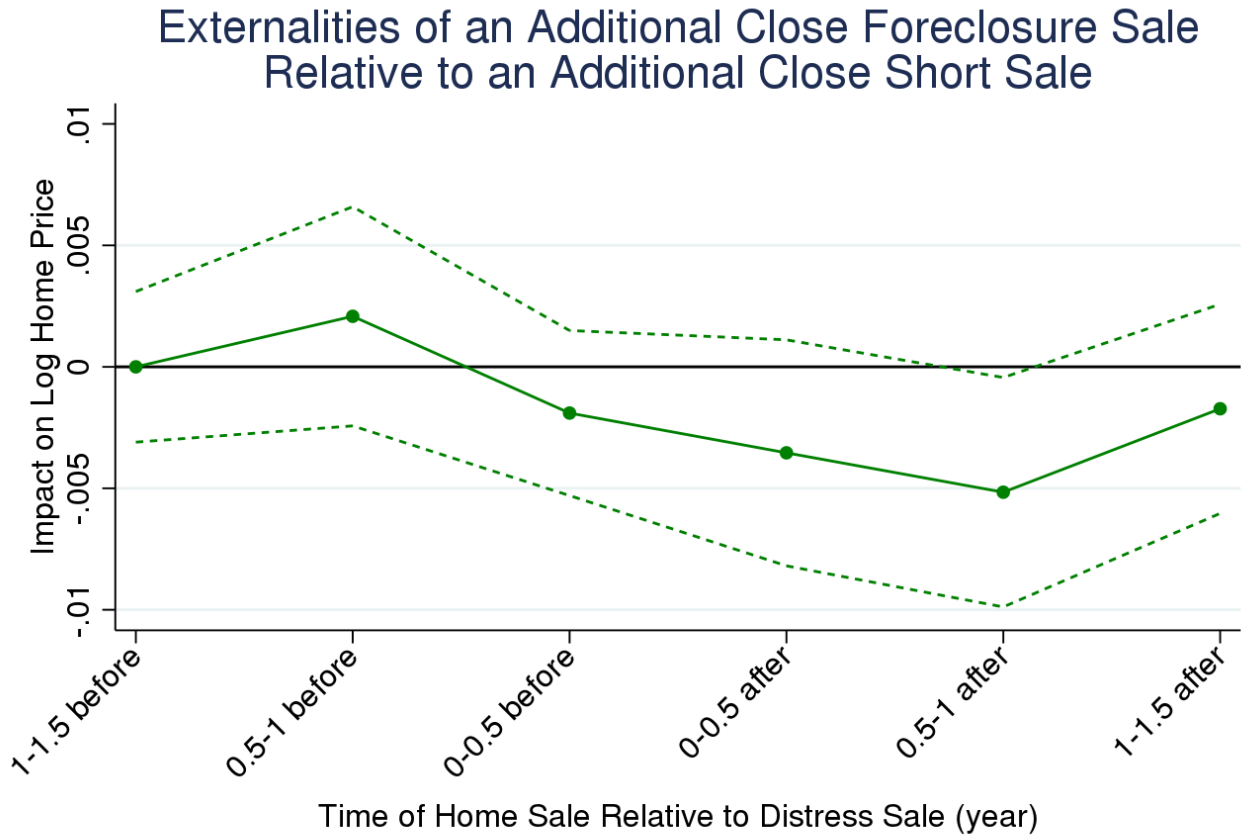
Notes: This figure presents the price externality of a foreclosure sale or a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and short sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics include square footage and age and their squared terms. Standard errors are clustered at the county level.

Figure 4 - Relative Price Externalities of Foreclosure Sales to Short Sales



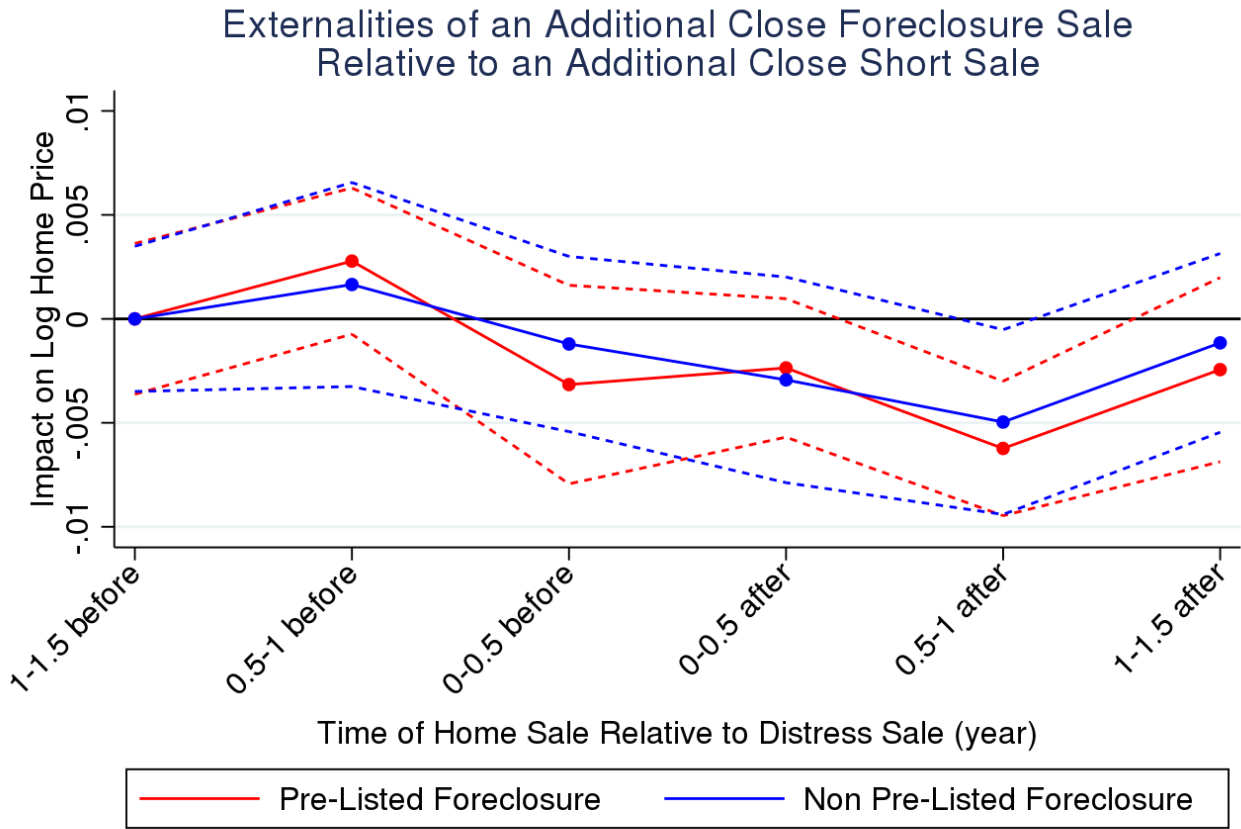
Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics include square footage and age and their squared terms. Standard errors are clustered at the county level.

Figure 5 - Relative Price Externality Using a Merged Transaction-Listing Sample



Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the merged MLS-DataQuick data set. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics include square footage and age and their squared terms. Standard errors are clustered at the county level.

Figure 6 - Relative Price Externality of Nonprelisted vs Prelisted Foreclosures



Data from merged DataQuick and MLS sample - Merged Homes Only; Single family residential home transactions from April 2009 - June 2013

Notes: This figure presents the price externality of a nonprelisted and a prelisted foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the merged MLS-DataQuick data set. A foreclosure is classified as prelisted if there was an active listing for that home two years prior to completion of the foreclosure process. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics include square footage and age and their squared terms. Standard errors are clustered at the county level.

Table 1 - Foreclosure and Short Sale Differences

Loan Type	Decision Maker	Goal
On balance sheet	Originating lender	Maximize recovery value of mortgage
GSE securitized	GSE	Maximize recovery value of mortgage
Private-label securitized	Servicer of loan	Maximize revenue from servicing fees while minimizing advances

Notes: This table presents information on the three different types of loans, based on what happened to the loan after origination.

Table 2 - DataQuick Summary Statistics

Panel A			
	Sale Counts by MSA		
	Foreclosures	Short Sales	All
Atlanta	92,137	21,503	454,642
Boston	20,657	18,451	336,774
Chicago	68,974	45,370	675,392
DC	40,436	30,693	452,009
Detroit	100,909	24,906	385,072
Los Angeles	101,451	78,104	788,979
Miami	61,069	51,704	507,505
Philadelphia	26,835	19,765	516,584
Phoenix	141,383	70,709	784,283
Seattle	35,537	27,529	411,837

Panel B			
	Transaction-Level Variables		
	Foreclosures	Short Sales	Difference
Count	689,388	388,734	-300,654
Sale Price	\$175,074	\$265,159	-\$150,565***
	(\$150,565)	(\$201,423)	
Square Footage	1,757	1,920	-163***
	(782)	(856)	
Age	38.5	37.5	1***
	(28.2)	(28.2)	

Significantly different from 0 at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents summary statistics on the base DataQuick transactions data set. Panel A contains counts of short sales, foreclosure sales, and all sales by MSA. Panel B presents means and standard deviations (in parentheses) on different home characteristics and a difference of means test for foreclosure vs short sale homes.

Table 3 - Merged MLS-DataQuick Summary Statistics

Panel A				
	Sale Counts by MSA			
	Nonprelisted Foreclosures	Prelisted Foreclosures	Short Sales	All
Atlanta	58,798	6,921	15,163	202,497
Boston	7,198	1,463	7,348	87,562
Chicago	34,471	10,611	31,937	222,949
DC	24,340	10,092	26,516	192,186
Detroit	59,153	8,413	17,018	170,663
Los Angeles	67,296	19,197	65,086	368,529
Miami	37,102	13,174	39,389	192,077
Philadelphia	7,239	2,466	8,013	119,246
Phoenix	100,703	23,635	58,655	339,711
Seattle	22,532	7,059	21,590	170,917

Panel B			
	Foreclosure Property-Level Variables		
	Nonprelisted	Prelisted	Difference
Count	418,832	103,031	315,801
Sale Price	\$169,972	\$203,411	-\$33,439***
	(\$145,106)	(\$164,441)	
Square Footage	1,751	1,833	-82***
	(761)	(838)	
Age	36.6	36.5	0.1
	(26.7)	(26.8)	
Bedrooms	3.37	3.45	-0.08***
	(0.82)	(0.87)	
Bathrooms	2.15	2.26	-0.11***
	(0.85)	(0.90)	

Significantly different from 0 at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents summary statistics on the merged MLS-DataQuick data set. Panel A contains counts of short sales, foreclosure sales, prelisted and nonprelisted, and all sales by MSA. Panel B presents means and standard deviations (in parentheses) on different home characteristics and a difference of means test for nonprelisted foreclosure vs prelisted foreclosure homes. Square footage and age comes from transaction data, while bedrooms and bathrooms come from listings data.

Table 4 - State Foreclosure Timelines and Judicial Foreclosure Classification

State	ABSNet Foreclosure Length	RealtyTrac Foreclosure Length	Judicial Foreclosure
AK	0.57		NJ
AL	0.35	0.26	NJ
AR	0.40	0.30	NJ
AZ	0.41	0.35	NJ
CA	0.45	0.50	NJ
CO	0.39	0.48	NJ
CT	0.79	0.57	J
DC	0.49		NJ
DE	1.08		J
FL	1.12	0.61	J
GA	0.33	0.30	NJ
HI	1.02		NJ
IA	0.91	0.46	J
ID	0.59		NJ
IL	0.86	0.87	J
IN	0.77	0.82	J
KS	0.51	0.42	J
KY	0.84	0.60	J
LA	0.87	0.35	J
MA	0.59	0.70	NJ
MD	0.51	0.46	NJ
ME	1.16		J
MI	0.33	0.19	NJ
MN	0.44	0.56	NJ
MO	0.25	0.16	NJ
MS	0.43		NJ
MT	0.74		NJ
NC	0.40	0.50	NJ
ND	0.84		J
NE	0.49		NJ
NH	0.42	0.30	NJ
NJ	1.29	0.93	J
NM	0.75	0.69	NJ
NV	0.49	0.46	NJ
NY	1.38	0.99	J
OH	0.89	0.65	J
OK	0.71	0.81	NJ
OR	0.59	0.49	NJ
PA	0.91	0.95	J
RI	0.47	0.33	NJ
SC	0.66		J
SD	0.70		NJ
TN	0.29	0.24	NJ
TX	0.37	0.17	NJ
UT	0.58	0.59	NJ
VA	0.31	0.25	NJ
VT	1.34		J
WA	0.57	0.39	NJ
WI	0.92	0.94	J
WV	0.51		NJ
WY	0.52		NJ

Notes: This table presents both the 2007 ABSNet and RealtyTrac foreclosure timeline measures for each state and the state’s judicial foreclosure classification. The judicial foreclosure classification comes from Gerardi, Lambie-Hanson, and Willen (2013).

Table 5 - ABSNet Summary Statistics

Panel A	Loan-Level Variables		
	Foreclosures	Short Sales	Difference
Count	867,763	90,502	777,261
Original Interest Rate	6.99% (2.36%)	7.53% (2.62%)	-0.54%***
LTV at Origination	81.0% (9.0%)	81.8% (13.6%)	0.8%***
Original Loan Balance	\$265,881 (\$180,272)	\$235,553 (\$199,270)	\$30,327***
FICO Score	662 (63)	664 (67)	-2***
Owner Occupied	78.9% (40.8%)	79.8% (40.2%)	-0.9%***
ARM	73.0% (44.4%)	59.1% (49.2%)	13.9%***
Home Price Change (Origination to Delinquency)	-20.3% (18.8%)	-25.6% (19.0%)	5.3%***

Panel B	Geographical-Level Variables					
	N	Mean	SD	10 th	50 th	90 th
2007 ABSNet Foreclosure Timeline in Years (State-Level)	51	0.66	0.29	0.35	0.58	1.08
2009 ABSNet Foreclosure Timeline in Years (State-Level)	51	0.86	0.37	0.44	0.71	1.41
2007 RealtyTrac Foreclosure Timeline in Years (State-Level)	36	0.52	0.24	0.24	0.49	0.93
Short Sale Share of All Distressed Sales (State-Level)	51	0.086	0.035	0.055	0.077	0.121
Log Employment (Zip Code-Level)	21,163	7.32	1.87	4.73	7.49	9.64
Log Income (Zip Code-Level)	21,163	22.02	2.36	17.93	22.61	24.45
2000 Rent-to-Income Ratio (Zip Code-Level)	21,163	0.013	0.003	0.010	0.013	0.017
Housing Market Turnover (Zip Code-Level)	13,096	4.27%	1.99%	2.24%	3.97%	6.47%

Significantly different from 0 at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents summary statistics on the ABSNet data set. Panel A presents means and standard deviations (in parentheses) on different loan-level variables. Panel B presents more detailed statistics on geographical-level, both state- and zip-code level, variables. 10th, 50th, and 90th represent the corresponding percentile.

Table 6 - Prelisted Foreclosure Discounts

	(1)	(2)	(3)	(4)
Foreclosure	-0.258*** (0.019)	-0.260*** (0.022)	-0.238*** (0.021)	-0.264*** (0.023)
Short Sale	-0.146*** (0.004)	-0.148*** (0.003)	-0.142*** (0.003)	-0.147*** (0.003)
Prelisted Foreclosure				0.021*** (0.005)
Property Characteristics	X	X	X	X
Tract by Year FE	X	X	X	X
Month FE	X	X	X	X
Foreclosure Sample	All	All	Prelisted Only	All
N	4,996,050	1,858,073	1,504,983	1,858,073
R ²	0.87	0.90	0.90	0.90

Notes: This table presents the estimates and standard errors (in parentheses) from a regression of log sale price on a foreclosure sale indicator and a short sale indicator to test for the difference in the foreclosure sale discount after controlling for prelisting. Column (1) presents the estimate without controlling for prelisting using the sample of transaction from the base DataQuick transactions data set, while column (2) uses the sample of transactions from the merged MLS-DataQuick data set. Column (3) then restricts foreclosure sales to only the prelisted ones, while column (4) uses all foreclosure sales but adds an additional indicator variable for prelisted foreclosure sales. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics include square footage and age and their squared terms in column (1). Bathrooms and bedrooms are added from the listing data in columns (2) - (4). Standard errors are clustered at the county level.

Table 7 - IV Estimate of the Difference Between Discounts

	(1)	(2)	(3)	(4)
	<i>Foreclosure</i>		<i>Log Sale Price</i>	
Percent Balance Outstanding	0.040*** (0.003)			
Foreclosure		-0.092*** (0.017)	-0.104*** (0.024)	-0.092** (0.045)
Property Characteristics	X	X	X	X
Tract by Half-Year FE	X	X	X	X
Month FE	X	X	X	X
Loan Origination Years	2004-2013	2004-2013	2004-2013	2007Q4-2011
Regression Type	OLS	OLS	IV	IV
N	265,147	265,147	265,147	26,871
R ²	0.31	0.91	0.91	0.92

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the estimates and standard errors (in parentheses) from the IV regression testing for the foreclosure discount relative to the short sale discount. The sample of transactions comes from the merged MLS-DataQuick data set. Column (1) reports estimates from the first stage OLS regression of a foreclosure sale indicator on the percentage of loan balance outstanding at listing. Column (2) reports the estimates of an OLS regression of log sale price on a foreclosure sale indicator variable using the IV sample. Columns (3) and (4) report the estimates from an IV regression of log sale price on a foreclosure sale indicator variable where the instrument is the percentage of loan balance outstanding at listing. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics include square footage and age and their squared terms, bathrooms, and bedrooms. Standard errors are clustered at the county level.

Table 8 - IV Estimate of the Impact of Foreclosure Timelines on Short Sales

	(1)	(2)	(3)	(4)	(5)
	<i>Foreclosure</i>	<i>Timeline</i>		<i>Short Sale</i>	
Judicial	0.632***	0.632***			
	(0.004)	(0.004)			
Foreclosure Timeline			-0.043***	-0.042***	-0.071***
			(0.008)	(0.008)	(0.013)
Controls	X	X	X	X	X
Year of Origin FE	X	X	X	X	X
Year of Distress FE	X	X	X	X	X
Servicer FE		X		X	X
Foreclosure Timeline Measure	ABSNet	ABSNet	ABSNet	ABSNet	RealtyTrac
Regression Type	OLS	OLS	IV	IV	IV
N	807,340	807,335	807,340	807,335	797,944

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the estimates and standard errors (in parentheses) from the IV regression testing for how foreclosure timelines affect the probability of a short sale. The sample of loans comes from ABSNet. Columns (1) and (2) report the results of the first stage estimate of the state-level foreclosure timeline on the judicial foreclosure indicator plus controls and fixed effects. Columns (3) - (5) report estimates from the 2SLS IV regression of an indicator for whether a delinquent loan ends in a short sale on the state-level foreclosure timeline and controls and fixed effects where the instrument is the judicial foreclosure indicator. Foreclosure timeline is measured in years. Columns (1) - (4) use the 2007 ABSNet measure of foreclosure timelines, while column (5) uses the 2007 RealtyTrac measure. Controls include original LTV, log original balance, original interest rate; indicators for adjustable rate mortgage, low FICO score (below 650), owner occupied, and state recourse law; zip code-level rent, log employment, log income, home price change, and housing turnover rates. The standard errors are clustered at the zip code level.

Table 9 - Impact of Foreclosure Timelines on Short Sales by Borrower

	(1)	(2)	(3)
Foreclosure Timeline	-0.050*** (0.009)	-0.021*** (0.004)	-0.014 (0.009)
Controls	X	X	X
Year of Origin FE	X	X	X
Year of Distress FE	X	X	X
Servicer FE	X	X	X
Borrower Type	Subprime	Alt-A	Prime
N	410,858	215,592	45,129

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the estimates and standard errors (in parentheses) from the IV regression of an indicator for whether a delinquent loan ends in a short sale on the state-level foreclosure timeline and controls and fixed effects where the instrument is the judicial foreclosure indicator split by borrower type. The sample of loans comes from ABSNet. Foreclosure timeline is measured in years. Controls include original LTV, log original balance, original interest rate; indicators for adjustable rate mortgage, low FICO score (below 650), owner occupied, and state recourse law; zip code-level rent, log employment, log income, home price change, and housing turnover rates. The standard errors are clustered at the zip code level.

Table 10 - Impact of Foreclosure Timelines on Short Sales by Servicer

	(1)	(2)	(3)	(4)
Foreclosure Timeline	-0.023*** (0.006)	-0.074*** (0.010)	-0.027*** (0.009)	-0.037*** (0.007)
Controls	X	X	X	X
Year of Origin FE	X	X	X	X
Year of Distress FE	X	X	X	X
Servicer FE	X	X	X	X
Servicer Type	Large	Medium	Small	BHC
N	380,107	290,811	136,417	470,949

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the estimates and standard errors (in parentheses) from the IV regression of an indicator for whether a delinquent loan ends in a short sale on the state-level foreclosure timeline and controls and fixed effects where the instrument is the judicial foreclosure indicator split by servicer type. The sample of loans comes from ABSNet. Foreclosure timeline is measured in years. Controls include original LTV, log original balance, original interest rate; indicators for adjustable rate mortgage, low FICO score (below 650), owner occupied, and state recourse law; zip code-level rent, log employment, log income, home price change, and housing turnover rates. The standard errors are clustered at the zip code level.

Table 11 - Testing for Borrower and Servicer Responses to Foreclosure Timelines

	(1)	(2)	(3)	(4)	(5)	(6)
Foreclosure Timeline	-0.031*** (0.007)	-0.036*** (0.007)	-0.033*** (0.007)	-0.042*** (0.008)	-0.047*** (0.008)	-0.046*** (0.007)
F Timeline X Rent	-8.059*** (1.498)		-8.062*** (1.498)	-2.630* (1.452)		-2.568* (1.451)
F Timeline X Orig Int Rate		0.502*** (0.115)	0.503*** (0.114)		0.903*** (0.111)	0.899*** (0.112)
Rent	3.875*** (0.567)	3.506*** (0.527)	3.895*** (0.566)	3.773*** (0.556)	3.681*** (0.526)	3.810*** (0.556)
Original Interest Rate	0.834*** (0.022)	0.839*** (0.022)	0.838*** (0.022)	0.834*** (0.022)	0.841*** (0.022)	0.840*** (0.022)
Controls	X	X	X	X	X	X
Year of Origin FE	X	X	X	X	X	X
Year of Distress FE	X	X	X	X	X	X
Servicer FE	X	X	X	X	X	X
Regression Type	OLS	OLS	OLS	IV	IV	IV
N	807,335	807,335	807,335	807,335	807,335	807,335
R ²	0.09	0.09	0.09			

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table test presents estimates and standard errors (in parentheses) from a linear probability model regression of an indicator for whether a delinquent loan ends in a short sale on the state-level foreclosure timeline, rent, original interest rate, and their interactions with foreclosure timeline, and controls and fixed effects. The sample of loans comes from ABSNet. All variables used in the interaction terms are demeaned. Foreclosure timeline is measured in years. Rent is the 2000 census zip code measure of rent-to-income. Original interest rate is the proxy for servicer advance since advances are a function of interest rates. Controls include original LTV and log original balance; indicators for adjustable rate mortgage, low FICO score (below 650), owner occupied, and state recourse law; zip code-level log employment, log income, home price change, and housing turnover rates. The standard errors are clustered at the zip code level.

Appendices

A Data Appendix

A.1 DataQuick - Home Transaction Data

DataQuick collects transaction data for each home that sells from the local assessor's office to create a nationwide data set. However, coverage is not consistent across the county. I focus my data sample on the 10 largest MSAs across America after filtering out MSAs where DataQuick coverage is lacking and limit my sample to only the largest MSA in each state. As a result, I end up with the following 10 MSAs (with the size rank in parenthesis):

- Los Angeles (2)
- Chicago (3)
- Washington, DC (6)
- Philadelphia (7)
- Miami (8)
- Atlanta (9)
- Boston (10)
- Phoenix (12)
- Detroit (14)
- Seattle (15)

My data sample begins in 2004, which is when DataQuick first began flagging short sales, and ends in 2013.

I clean up duplicates in the same manner as Campbell, Giglio, and Pathak (2011). Then I drop all transactions with a 0 sale price and all nonarms-length transactions except REO to lender transactions where the lender takes ownership of a home after it has been foreclosed. Additional

cleanings include dropping homes that cannot be accurately geocoded, dropping homes that sold multiple times in a 30-day window, dropping homes that experienced a 4 times price change between transactions, and winsorizing home prices at the 1% and 99%.

When cleaning and tabulating the distress sales, I use the DataQuick distress indicator field to identify short sales and any foreclosure-related transaction. Short sales are imputed using a proprietary DataQuick model since they may not always be reported from the assessor office. For homes that are foreclosed on, the home should then either become an REO or get sold at a foreclosure auction to a third party. After a home becomes an REO, then it can be sold as an REO to a third party. These two REO-type transactions should occur back to back without any regular transactions in between. I drop homes where I observe a regular transaction immediately before the sale of an REO property or immediately after an REO-to-lender transaction.

A.2 Transactions-Listings Data Merge

I obtain MLS data for the same 10 MSAs that I selected for my DataQuick sample from Altos Research. Every week, Altos Research takes a snapshot of MLS to obtain listing info on all the listed homes. They assign a unique ID code for each property based on the address and another unique ID code based on the listing. For each snapshot, they provide the snapshot date, the listing price at that time, and the days on market during that week. If a listing is continuously active from week to week, both unique ID codes will remain constant.

Home addresses are provided by both data sets, and this is the only field I can use to merge the two data sets. To simplify the merge, I geocode the addresses from MLS using the same address locator used to geocode DataQuick so I can match on latitudes and longitudes. The advantage of merging on latitude and longitude is that, while there are different ways to write the full address of a home, geocoding produces the same coordinates, which leads to more accurate merging. For example, 555 State St can also be written as 555 State St. or 555 State Street, but after geocoding the different addresses, they will all produce the same coordinates. For any homes that cannot be geocoded, then I merge on the raw address. Since the listing data does not begin until October 2007, I drop all transactions that occurred before then.

Before merging the data, I first clean up the listing data. For each continuous listing, I collapse the weekly panel into a cross section with one observation per continuous listing and record the

first date of listing, starting price, beginning time on market, last date of listing, ending price, and ending time on market. Each continuous listing is also given a unique identifier composed of a property ID, the unit number, and a list ID. Sometimes one continuous listing may have been split into multiple listings with its own identifier in the data, especially if the address of the home is written a different way or if there is a lapse in coverage in the data. I use the time on market and listing date differences between the multiple listings to determine if they should be one.¹ I combine all these multiple listings into one by assigning them all the same unique identifier. I also combine multiple listings for the same home if the time gap between one listing ending and the other starting is less than 28 days to account for gaps in coverage.

Before merging, I also clean up street names from the MLS data so I can merge homes that cannot be geocoded. The street address should be split into six fields: house number, street direction, street name, street type, street post direction, and unit number. Unfortunately, the complete address is not always perfectly parsed out into these different fields so I need to clean and parse out the address as needed. I also abbreviate all street types to make it consistent with the DataQuick field.

After merging the two data sets together, I have a set of all homes that have ever been listed in the MLS data at any point, even if there is not a listing for every transaction. Then, I remove all homes that are not classified as single-family homes or have a unit number in DataQuick or have multiple units in the MLS data. The resulting set of homes are the ones that I use as my merged data set to address unobserved home quality.

From this data set, I can identify the foreclosed homes that had a listing. To do so, I first remove all homes that never had a foreclosure-related transaction. Then for the remaining homes, I find the transaction that corresponds to each listing. When a listing matches to multiple transactions, I keep the transaction that occurred most recently after the listing has ended. Then for transactions that match to multiple listings, I keep the last listing to end before the transaction date. Lastly, I drop any listing that ended more than 2 years before a transaction because long foreclosure delays could cause a big time gap between the removal of a failed short sale listing and the sale

¹For example, suppose a listing for 555 State St exists from January 1-29 and the time on market for this listing goes from 0 to 28 days. Then there is a listing for 555 State Street from February 5 to February 26 with the starting time on market equal to 35 days. These two listings should be the same continuous listing for the same home, but they were given two different unique IDs because the street was written differently.

of the foreclosed home. After having a one-to-one match of listing to transaction, then I label any foreclosure sale as being listed if I find the listing associated with the REO-to-lender transaction or foreclosure auction transaction that occurred for that foreclosed home.

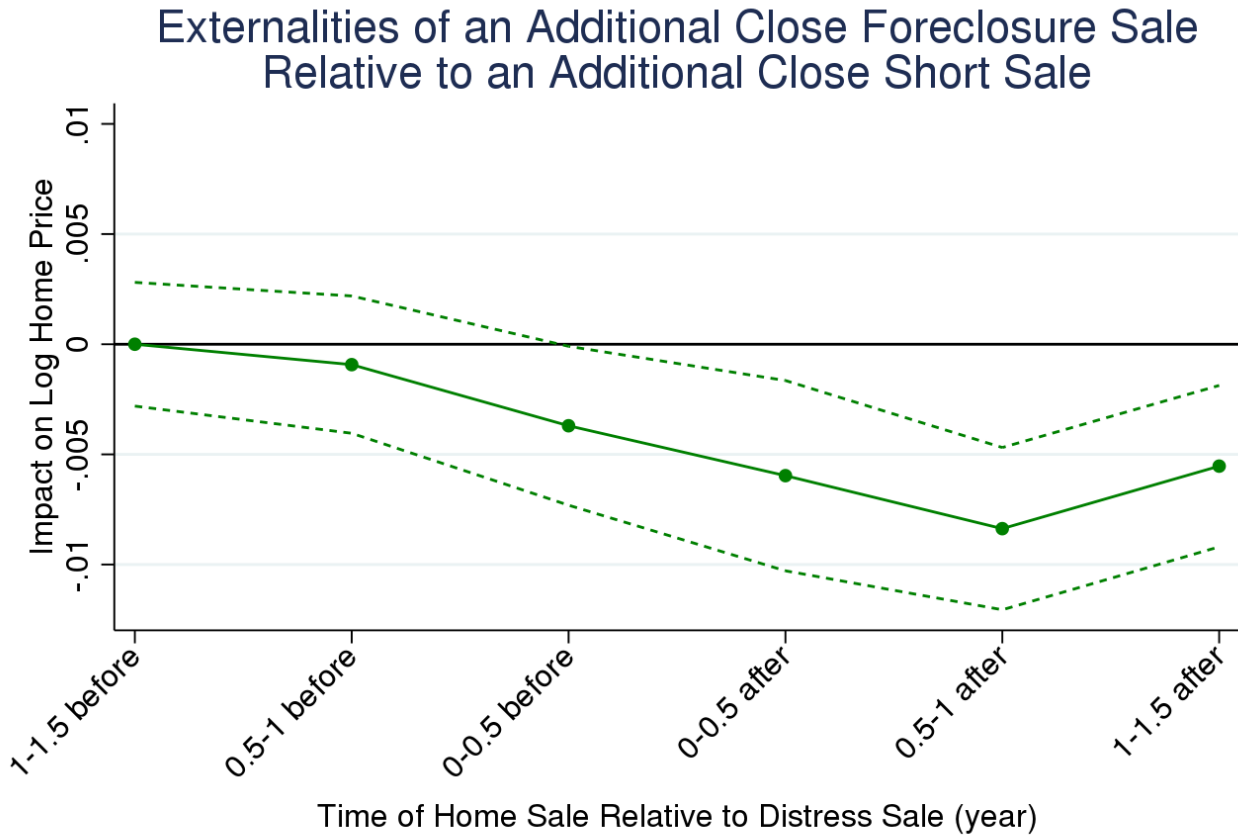
A.3 ABSNet - Loan Performance Data

ABSNet has loan performance data for mortgages that are a part of private-label securitization deals. Coverage is fairly consistent across the county so I do not place any geographical restrictions. Since the focus of my study is on distressed mortgages resulting from the housing crash, I focus my sample on mortgages that originated in 2003-2007 and became 90-days delinquent between 2008 and 2013. Additional filters I apply are: use first lien loans; use loans for single-family homes; use loans with LTV at origination between 20% and 100%; eliminate loans where the borrower's credit score is missing; eliminate loans in securitization deals with no short sales. I also winsorize original loan balance and original interest rate at 1% and 99%.

While the data have flags for mortgages that end in a short sale, there are none for mortgages ending in foreclosures. The data do provide dates for when a mortgage begins foreclosure, becomes REO, and is liquidated that I can use to infer foreclosures. A loan can begin foreclosure but not end in a foreclosure if the borrower is able to sell the home or resume payments before the foreclosure process ends. As a result, I only classify a mortgage as ending in foreclosure if it has either an REO date or a liquidation date or both in addition to having a foreclosure start date. I assert that mortgages with only a foreclosure start and liquidation date are for homes that sold at a foreclosure auction so the home never became an REO.

B Robustness Checks

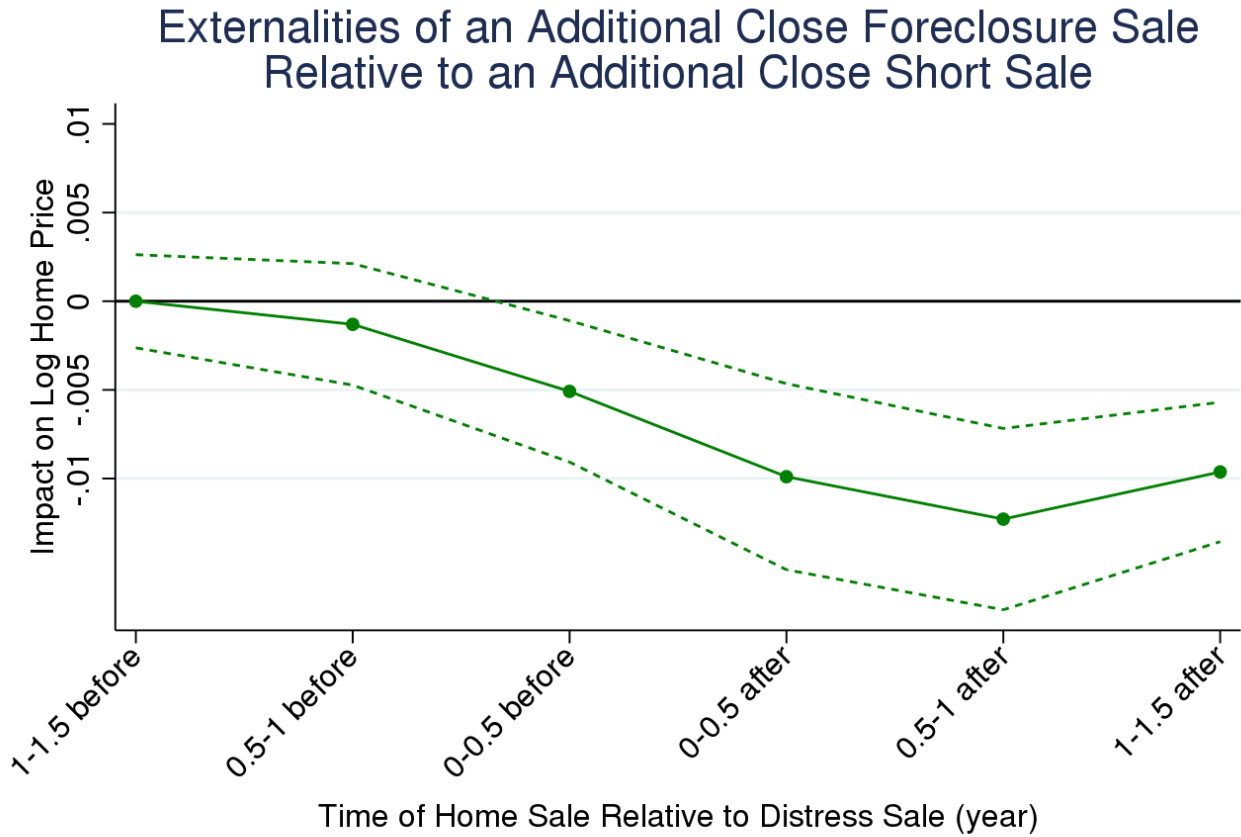
Figure A1 - Relative Foreclosure Externality - Control for all Sale Counts



Data from DataQuick; Single family residential home transactions from July 2005 - June 2012; Include nearby non-distress sale counts

Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Counts of nondistressed sales at both the close and far distance are also included as controls. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. Standard errors are clustered at the county level.

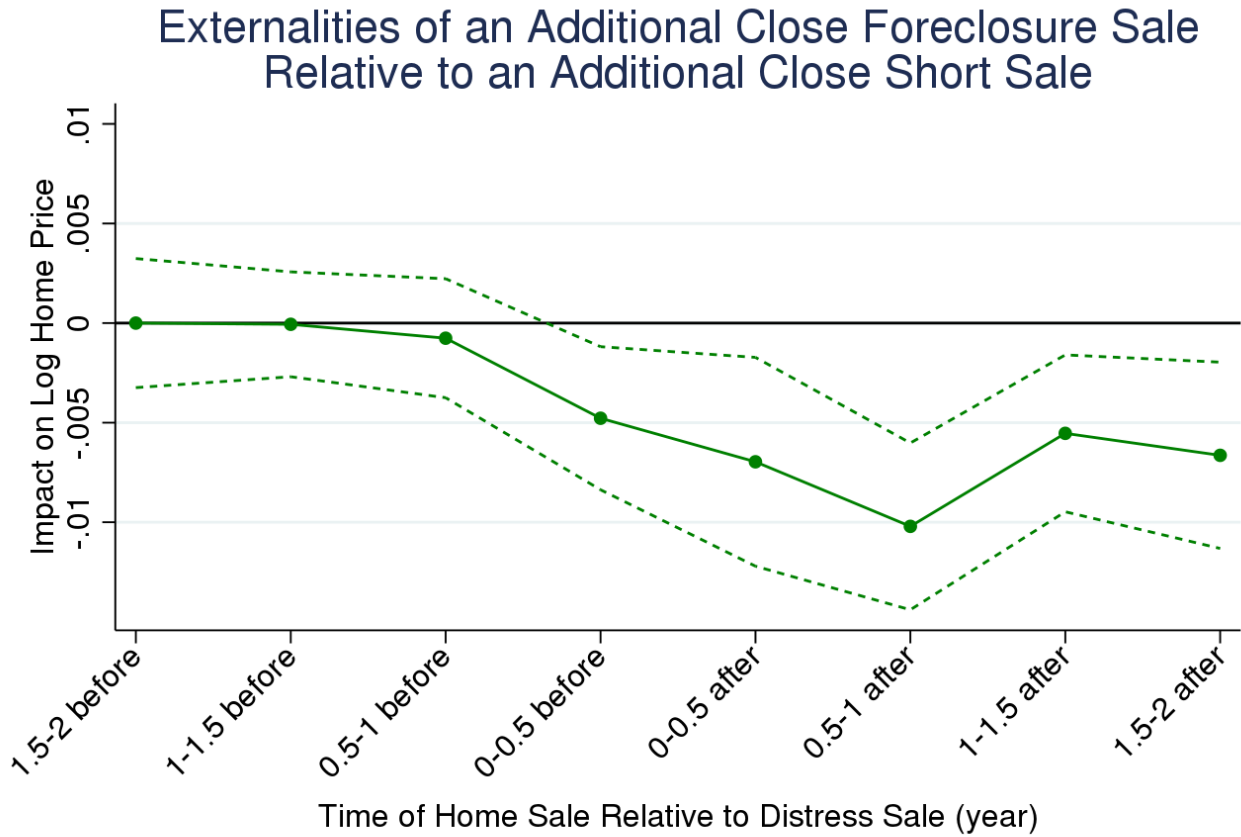
Figure A2 - Relative Foreclosure Externality - Far Distance at 0.33 Miles



Data from DataQuick; Single family residential home transactions from July 2005 - June 2012; Far distance increased to 0.33 miles

Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Close is within 0.10 miles, and far is within 0.33 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. Standard errors are clustered at the county level.

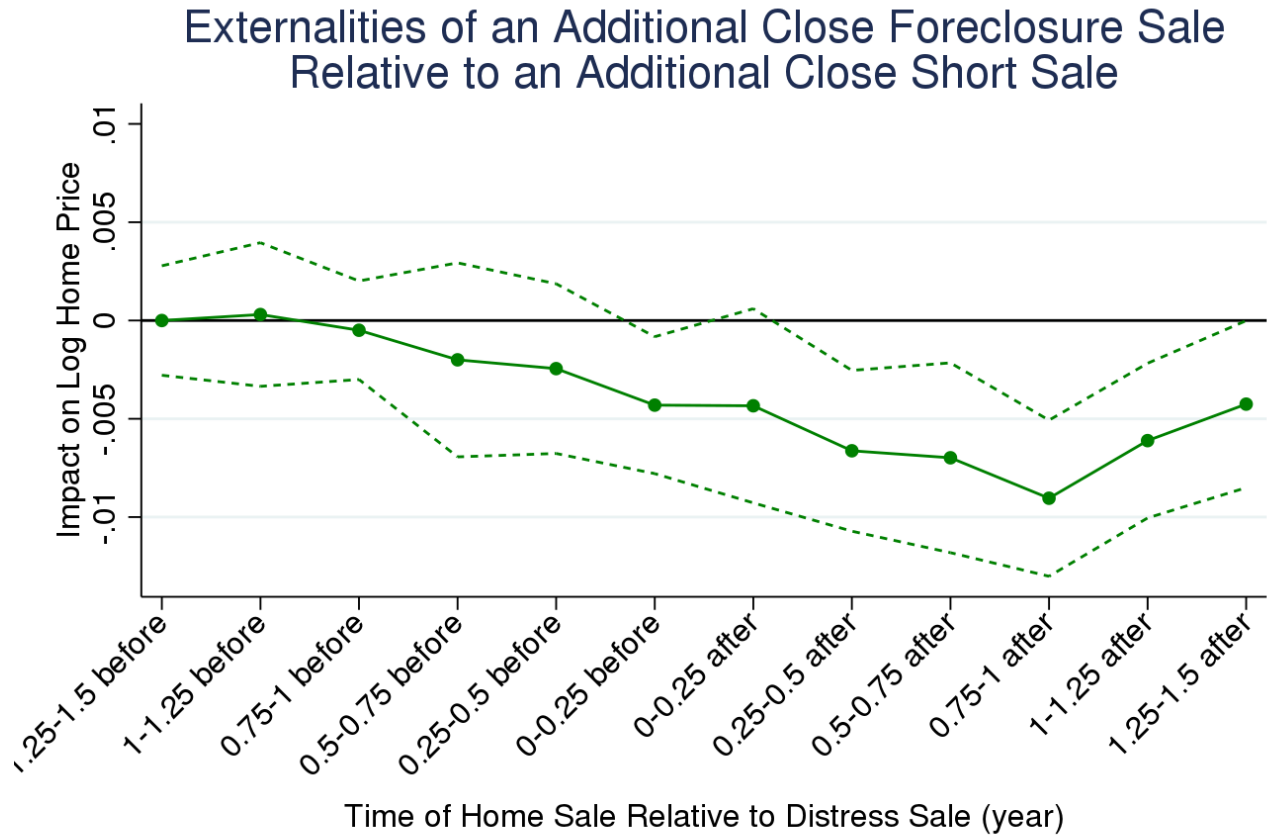
Figure A3 - Relative Foreclosure Externality - 4-Year Window



Data from DataQuick; Single family residential home transactions from January 2006 - December 2011

Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a four-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. Standard errors are clustered at the county level.

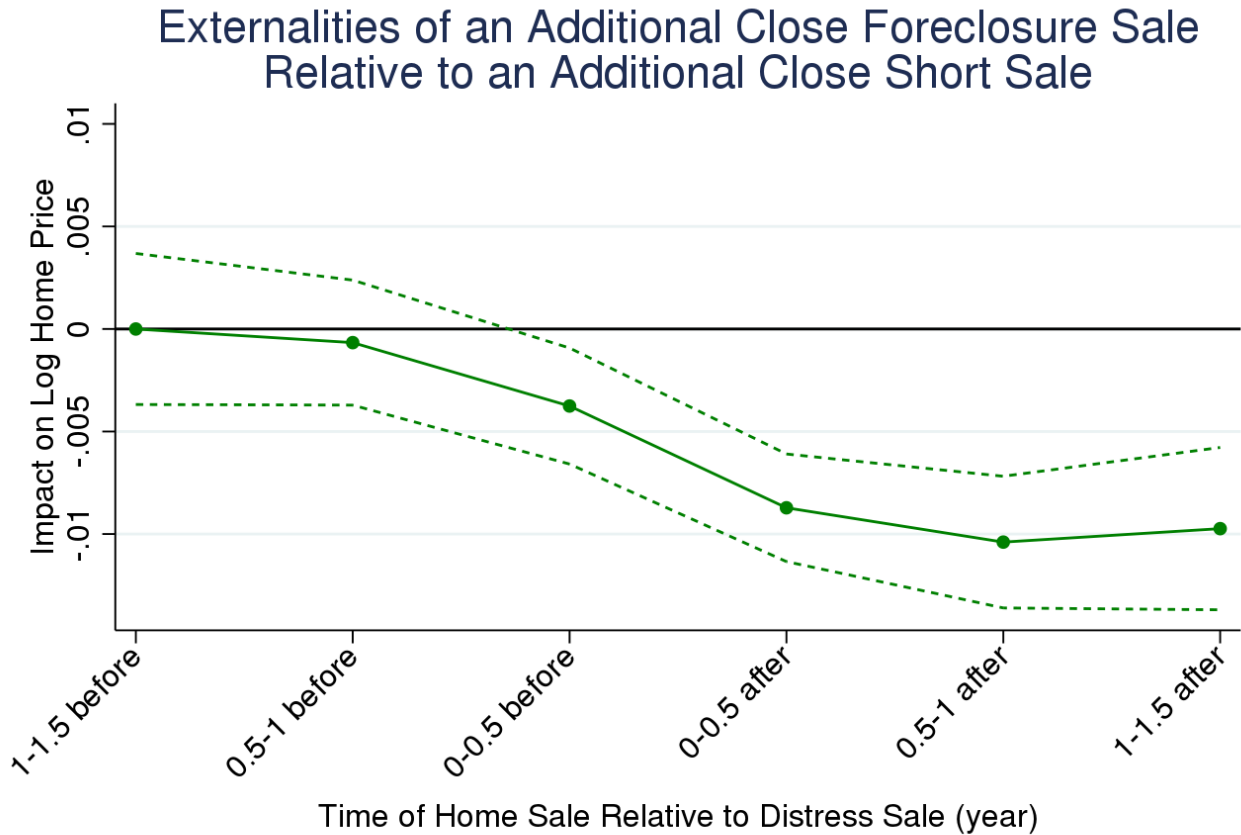
Figure A4 - Relative Foreclosure Externality - Quarterly Periods



Data from DataQuick; Single family residential home transactions from July 2005 - June 2012

Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each three-month interval relative to the sale date. All regressions include tract by quarter-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. Standard errors are clustered at the county level.

Figure A5 - Relative Foreclosure Externality - All Home Types



Notes: This figure presents the price externality of a foreclosure sale relative to that of a short sale by plotting the estimates and 95% confidence intervals from a regression of log home prices on close and far foreclosure sale and distress sale counts that occurred within a three-year window around the sale of each home. The sample of transactions comes from the base DataQuick transactions data set. Close is within 0.10 miles, and far is within 0.25 miles. The estimates represent how sale prices are affected by a close foreclosure sale relative to a close short sale that occurred in each six-month interval relative to the sale date. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. All home types are included in data set, and home type fixed effects are included in the regression. Standard errors are clustered at the county level.

Table A1 - Foreclosure Sale and Short Sale Discounts by MSA

	(1)	(2)	(3)	(4)	(5)
Foreclosure	-0.271*** (0.004)	-0.328*** (0.005)	-0.339*** (0.004)	-0.226*** (0.004)	-0.331*** (0.003)
Short Sale	-0.174*** (0.003)	-0.157*** (0.004)	-0.121*** (0.003)	-0.144*** (0.003)	-0.104*** (0.004)
MSA	Atlanta	Boston	Chicago	DC	Detroit
N	739,380	500,265	497,053	773,343	398,367
R ²	0.88	0.86	0.82	0.89	0.80
Foreclosure	-0.145*** (0.002)	-0.274*** (0.003)	-0.367*** (0.005)	-0.192*** (0.004)	-0.248*** (0.003)
Short Sale	-0.130*** (0.001)	-0.156*** (0.003)	-0.117*** (0.003)	-0.151*** (0.003)	-0.131*** (0.002)
MSA	Los Angeles	Miami	Philadelphia	Phoenix	Seattle
N	445,669	327,614	529,912	435,088	349,359
R ²	0.80	0.74	0.84	0.83	0.80
Property Characteristics	X	X	X	X	X
Tract by Year FE	X	X	X	X	X
Month FE	X	X	X	X	X

Notes: This table presents the estimates and standard errors (in parentheses) from a regression of log sale price on a foreclosure sale indicator and a short sale indicator to test for the discount associated with foreclosure sales and short sales split by MSA. The sample of transactions comes from the base DataQuick transactions data set. All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. Standard errors are clustered at the census tract level.

Table A2 - Foreclosure Sale and Short Sale Discounts by Property Type

	(1)	(2)	(3)	(4)	(5)	(6)
fore	-0.265*** (0.017)	-0.262*** (0.017)	-0.259*** (0.019)	-0.214*** (0.027)	-0.358*** (0.022)	-0.228*** (0.021)
shortsale	-0.154*** (0.006)	-0.151*** (0.006)	-0.146*** (0.004)	-0.154*** (0.006)	-0.171*** (0.029)	-0.139*** (0.011)
Property Characteristics	X	X	X	X	X	X
Tract by Year FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Property Type FE		X				
Property Type	All	All	Single-Family Res	Dup, Trip, Quad	Apartment	Condo
N	7,095,948	7,095,948	4,899,854	116,745	87,674	1,923,065
R ²	0.85	0.86	0.88	0.87	0.86	0.90

Notes: This table presents the estimates and standard errors (in parentheses) from a regression of log sale price on a foreclosure sale indicator and a short sale indicator to test for the discount associated with foreclosure sales and short sales split by MSA. The sample of transactions comes from the base DataQuick transactions data set. Unlike the definition of single-family residential used in the main analysis, homes classified as single-family residential in column (3) no longer include duplexes, triplexes, and quadplexes. Instead, these 3 types are classified in their own category in column (4). All regressions include tract by half-year and month fixed effects and property characteristics. Property characteristics are square footage and age and their squared terms. Standard errors are clustered at the county level.