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Abstract

This paper tests for the spillover effects of foreclosure within broad neighborhoods. The best evidence that foreclosures have causal, spillover effects on housing prices and future foreclosures suggest highly localized spillover effects that are modest in magnitude, but these effects could multiply when the density of spillovers is high leading to larger aggregate effects in broader neighborhoods. We test this proposition by developing a proxy for the fraction of housing units/mortgages that are expected to be in negative equity during the crises. This proxy exploits the timing of purchases in each tract during the run up to the crisis, and we show that our source of identification, within tract variation in purchases over time, is not predicted the observed mortgage attributes. Our estimates suggest that 67 percent of the increase in the across tract dispersion in the recording of new foreclosure recordings can be explained by the spillover effects of the contemporaneous stock of foreclosures.

Key words: Foreclosure, Negative Equity, Neighborhood Spillovers, Mortgages, Housing Crisis
JEL Codes: G2, R2, R3

Foreclosure Spillovers within broad Neighborhoods

Several important papers have documented the effect of neighborhoods specifically and networks more generally on financial decisions. Research on bankruptcy is suggestive of a role for neighborhood level networks in financial decisions regarding debt payments (Scholnik 2013; Dick et al. 2008; Cohen-Cole and Duygan-Bump 2008).[1] Hong et al. (2004) show that individuals who interact more with their neighbors or attend church are more likely to invest in the stock market, and Brown et al. (2008) demonstrate that metropolitan rates of stock market participation influence individual stock market participation. Workplace peers (Nanda and Sorenson 2010) and business school networks (Lerner and Malmendier 2013) are important for decisions to engage in entrepreneurship, and workplace peers have also been shown to influence retirement savings decisions (Beshears et al. 2015, Duflo and Saez 2003).[2]

More specifically, a growing literature examines the spillover effects of foreclosures on spatially proximate housing prices and the likelihood of future foreclosures. Many studies have documented high contemporaneous rates of foreclosure and heavily depressed housing prices in neighborhoods that have experienced a large number of foreclosures including Immergluck and Smith (2006), Leonard and Murdoch (2009) and Rogers and Winter (2009) for housing prices and Goodstein et al. (2001) and Bradley at al. (2015) for foreclosures. Unfortunately, it is difficult to disentangle the effects of foreclosure rates at the neighborhood level from the effect of economic factors and household unobservables that contribute to those foreclosure rates.

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[1] See Fay et al. (2002) and Gross and Souleles (2002) for more general analyses of the bankruptcy decision.

[2] Earlier studies on other effects of social interactions include studies of crime (Glaeser, Sacerdote and Scheinkman 1996), employment (Topa 1999; Bayer, Ross, and Topa 2008), welfare usage (Bertrand, Luttmer, and Mullainathan 2000; Cohen-Cole and Zanella, 2008), pre-natal care (Aizer and Currie 2004), health behaviors (Fletcher and Ross 2012) and academic outcomes (Fletcher, Ross and Zhang 2013). See recent surveys by Ioannides and Topa (2010) and Ross (2011).

In response, many recent studies have exploited high frequency data over space and time to identify the causal effect of foreclosure over very localized housing markets. These studies include high dimensional fixed effects to control for neighborhood unobservables and so identify the effect of foreclosures on housing sale prices located within a specified distance of the foreclosure, between 250 feet and one half mile (Schuetz et al. 2008; Harding et al. 2009; Campbell et al. 2011; Anenberg and Kung 2014; Hartley 2014; Gerardi et al. 2015).[3] The studies also tend to control for neighborhood trends, and typically find modest effects of nearby foreclosures on housing prices.[4]

A smaller literature investigates whether social networks or other non-price spillovers influence foreclosure rates within neighborhoods. Guiso et al. (2013) find that individuals who know someone who defaulted on their mortgage are 82 percent more likely to state their intention to default. Following the literature on prices, Towe and Lawley (2013) identify the causal effect on foreclosure of earlier foreclosures among an individual's 13 to 25 closest neighbors by conditioning on the broader neighborhood. Munroe and Wilse-Samson (2013) and Gupta (2016) both use instrumental variable approaches, random assignment of chancery-court judges to foreclosure cases and the contractual terms of adjustable-rate mortgages respectively, to identify the causal effect of foreclosure over and above any price effects of foreclosures. Both studies again focus on very localized effects, i.e. foreclosures within 0.1 miles of a household. All three studies find substantial evidence that preceding foreclosures raise the likelihood that other nearby households experience foreclosure. If foreclosure activity is sufficiently dense in a neighborhood,

[3] Bayer, Ross and Topa (2008) argue that thin housing markets and limited information on micro neighborhoods make it difficult for households to systematically sort into specific houses or residential blocks conditional on broader neighborhoods, and support this assertion empirically with balancing tests.

[4] One exception is Lin et al. (2009) who find large housing price effects, but this difference may be because they do not control for neighborhood trends unlike many of the other studies cited.

these localized network effects could spill over space and multiply leading to higher average foreclosure rates for the entire neighborhood.

However, in spite of the growing evidence of causal effects of foreclosures on very localized housing markets, we do not know whether these localized spillovers and/or neighborhood spillovers in general contribute substantially to the large conditional correlations between overall neighborhood foreclosure rates and the likelihood of future foreclosures in the same neighborhood. Therefore, given the high correlation between negative equity and foreclosure, we develop an exogenous proxy for the share of households in negative equity for each neighborhood and quarter during the financial crisis in order to test for an aggregate effect of expected neighborhood foreclosure activity on the likelihood of future foreclosure notices in the same neighborhood.

Specifically, we develop a prediction for negative equity for all housing units purchased in the run up to the housing crisis that does not depend upon either neighborhood housing prices or the Combined Loan to Value (LTV) ratios selected by the buyers in that neighborhood.[5] This prediction exploits the timing of when individuals purchased housing in each neighborhood and combines this information with the time path of housing prices and the distribution of LTV's for the overall housing market during this time period. For example, if a neighborhood happens to have more transactions near the peak of the market, then this neighborhood will be predicted to have more housing units in negative equity early in the crisis. We also verify that there is at most a weak within tract correlation between the volume of housing transactions in a given quarter and the attributes of the mortgages originated during that quarter.

We specify a model of foreclosure as a function of the predicted share of mortgages experiencing negative equity controlling for individual risk variables including contemporaneous

[5] The combined loan to value ratio is the ratio of the total value of all liens on the property at the time of purchase to the sales price of the property. For convenience, LTV is used as a short-hand for this ratio.

LTV for the individual mortgage plus purchase quarter and year by census tract fixed effects and purchase quarter and year by crisis quarter and year fixed effects. This fixed effect structure allows each cohort of loans in the market to have a unique time path of foreclosures during the crisis and allows for heterogeneity in the unobservables of buyers over time (purchase quarter and year) in each census tract in terms of average foreclosure risk. The model is identified by variation across crisis quarters and across census tracts in the expected share of households who are predicted to be experiencing negative equity. As a robustness test, we also add an additional set of controls where we interact crisis year dummy variables with pre-determined census tract observables allowing for tract specific trends over observables during the crisis period.

We estimate models for whether a housing unit received the first foreclosure notice, or Notice of Trustee Sale (NOT), in a given quarter using a sample of single family housing units that sold as arm's length transactions between the third quarter of 2001 and the second quarter of 2006. The first foreclosure notice is based on foreclosure notices on those units issued between the third quarter of 2006 and the second quarter of 2010 for San Diego County.[6] Our instrument is strongly predictive of the total number of units in a census tract that have experienced at least one NOT by the end of the quarter. We estimate both reduced form models and instrumental variable models, the later requiring the assumption that neighborhood levels of negative equity only influence the likelihood of a first NOT through the number of units in foreclosure, i.e. units having already received a NOT since the on-set of the crisis.

[6] While our model relates current foreclosure likelihood to a proxy for the anticipated likelihood of foreclosure levels at that time in the neighborhood, our model does not explicitly solve the reflection problem where Manski (1993) argues that it is impossible to disentangle the effects of exogenous neighborhood or peer attributes from endogenous effects arising from the choices made by those neighborhood peers. We face the same limitation in that we cannot explicitly distinguish between the effects of neighborhood negative equity levels and the effects of preceding foreclosure decisions by residents in the neighborhood. However, we anticipated that both neighborhood negative equity levels and neighborhood foreclosures both operate in the same direction, and our proxy captures the combined effect of both spillover mechanisms. We obtain lower bounds on the overall effects of neighborhood negative equity on foreclosure by estimating reduced form models.

The estimate spillover effects are quite large. a one standard deviation change in the share of units in negative equity is associated with an 86% increase in the likelihood of a unit purchased during our pre-crisis period entering foreclosure in the next quarter over a base of 0.7 percentage points using the reduced form estimates. Similarly, a one standard deviation in the number of units having received a NOT implies between a 64% increase in the likelihood of entering foreclosure in a quarter. The magnitude of both the reduced form and IV estimates are very stable as we add controls for mortgage attributes, and the magnitude of the IV estimates are unaffected by the inclusion of the tract specific foreclosure trends even though the instruments become somewhat weak after the inclusion of trends. We also assess the magnitude of these effects by comparing the increases in across neighborhood dispersion in the stock of mortgages with foreclosure notices, and find that the increase in the stock dispersion can explain 67% of the increase in the dispersion of new foreclosure filings, consistent with neighborhoods following different foreclosure paths in part because the effects of past foreclosures are having spillover effects on other mortgages. Further, even as housing prices recover, these neighborhood spillover effects contribute to persistently high rates of new foreclosures.

We also examine whether the spillover effects vary by neighborhood type. We interact the predicted fraction of units in negative equity with either the tract share black, share Hispanic or share of households in poverty either including those variables directly in the reduced form estimates or using them as instruments for the interaction of neighborhood foreclosure levels with the same tract attributes. The reduced form estimates suggest that the foreclosure effects of negative equity are much larger in these disadvantaged neighborhoods with the differences primarily being driven by neighborhood share Hispanic. However, the two stage least squares estimates are relatively constant across different types of neighborhoods. These results are consistent with negative equity being a stronger predictor of foreclosure in disadvantaged neighborhoods so that the larger reduced form estimates are deflated by a larger first stage.

In summary, we find large spillover effects of foreclosures in the San Diego housing market during the housing crisis with increases in negative equity and foreclosure rates being associated with large increases in the baseline rate of foreclosure. The magnitude of these results are very stable to the inclusion of observed mortgage risk factors and robust to the inclusion of tract specific trends in foreclosure rates. The results are also broad based occurring in both disadvantaged neighborhoods and neighborhoods with smaller fractions of minority residents and families in poverty.

Methodology

Predicting Neighborhood Levels of Negative Equity

In this section, we construct our instrument or proxy for neighborhood foreclosure risk $\widehat{NB}_{gt}$ as the predicted level of negative equity in each neighborhood *g* and crisis quarter by year *t*. Specifically, we calculate the fraction of home purchases likely to be in negative equity in each current quarter at the census block group or tract level based on the quarter of purchase, the market wide distribution of initial Combined Loan to Value (LTV) ratios, and time pattern of market wide housing prices.

First, we develop the market wide housing price index by estimating a traditional hedonic sales price model:

$$P_{jt} = \beta W_j + \delta_t + \varepsilon_{jt} \quad (1)$$

where P_{jt} is the logarithm of the sales price of house *j* at quarter in year *t*, W_j is a vector of housing attributes of house *j*, and δ_t is a quarter by year *t* fixed effect. The resulting price index ($\bar{P}$) is:

$$\bar{P}_t = \frac{Exp(\bar{\delta}_t^5)}{Exp(\bar{\delta}_1^5)} \quad (2)$$

where $\bar{\delta}_t^5$ is a five quarter moving average of $\hat{\delta}_t$ centered on quarter *t*. This price index is used to calculate both the current LTV of individual housing units and the predicted levels of negative equity. We use market wide price indices even for the current LTV on individual units since using a neighborhood level price index would capture the effects of foreclosures on local housing prices, which is a phenomenon that we intend to include within the estimated neighborhood spillovers.

Second, we define and calculate the market wide distribution of initial LTV ratios over LTV bin (*b*), by purchase quarter (*p*), as follows:

$$D_{bp} = Fr(\overline{LTV}_{b-1} < LTV_{jp} \leq \overline{LTV}_b) \tag{3}$$

where *Fr* represents the fraction of individual property sales (*j*) in purchase quarter (*p*) that fall between the lower bound $\overline{LTV}_{b-1}$ and the upper bound $\overline{LTV}_b$ of each LTV bin *b*. For each bin, we can then calculate whether the loans in that bin would be in negative equity in crisis quarter *t* if the loans had been originated in pre-crisis quarter *p*. Specifically, using the price index from equation (2), a mortgage in a given bin is predicted to be in negative equity (ignoring amortization) if

$$\overline{LTV}_{b-1} * \frac{\bar{P}_p}{\bar{P}_t} > 1 \tag{4}$$

Then, for each quarter during the crisis (*t*), we calculate a predicted fraction of home purchases during the run up to the crisis that are likely to be in negative equity. We create this fraction by summing the product of the share of transactions (D_{bp}) associated with a specific purchase quarter LTV bin (*b*) and a binary indicator (*I*) for whether the current LTV is in negative equity over all bins for a given purchase quarter/crisis quarter combination. Next, we multiply this sum (the fraction of purchases predicted to be in negative equity) by the number of transactions N_{gp} in a given purchase quarter and neighborhood to obtain the number of houses in negative equity in each neighborhood (*g*), purchase quarter (*p*), and current quarter (*t*). We then sum the numbers over all purchase quarters and scale by the number of transactions in the neighborhood during the entire pre-crisis period (N_g):

$$\widehat{NB}_{gt} = \frac{1}{N_g}\sum_{p=1}^{P} N_{gp}\left(\sum_{b=1}^{B} D_{bp} I\left(\overline{LTV}_{b-1} * \frac{\bar{P}_p}{\bar{P}_t} > 1\right)\right) \tag{5}$$

Our instrument is identified by differences in the timing of purchases at the neighborhood level. Neighborhoods with higher purchase volumes early in the pre-crisis period (prior to rapid housing price appreciation) will exhibit lower measures of neighborhood foreclosure risk after the start of the crisis. Note also that our instrument employs $\overline{LTV}_{b-1}$—the lower bound of the LTV bin—in order to obtain the most conservative estimates of negative equity. B denotes the number of bins, and P denotes the number of pre-crisis quarters.

Estimation Equations

To examine whether individual housing units are more likely to be foreclosed in neighborhoods with higher foreclosure risks, we regress an indicator for receiving a first Notice of Trustee Sale (NOT) on our predicted level of negative equity, $\widehat{NB}_{gt}$. Since $\widehat{NB}_{gt}$ varies by neighborhood and crisis quarter, we estimate the model using a difference-in-differences strategy by including fixed effects associated with neighborhood g and associated with crisis quarter t. Specifically, we include neighborhood g by purchase quarter p (during the pre-crisis period) fixed effects (α_{gp}) to allow for differences in foreclosure rates across each quarter cohort of mortgages within each neighborhood. We also include crisis quarter t by purchase quarter p fixed effects (δ_{pt}) so that each purchase quarter cohort of loans has a different market wide time profile of foreclosure over the foreclosure crisis period.

$$NOT_{igpt} = \beta\widehat{NB}_{gt} + \theta LTV_{igpt} + \alpha_{gp} + \delta_{pt} + \varepsilon_{igpt} \tag{6}$$

where NOT_{igpt} is whether the housing unit i received a first NOT in crisis quarter t and LTV_{igpt} is the current combined loan to value ratio capturing the current level of negative equity.

If we are willing to impose the assumption that neighborhood negative equity only influences foreclosures through the number of on-going foreclosures, we can estimate an instrumental variables specification using Two-Stage Least Squares (2SLS). The first stage regresses a variable for the number of mortgages that have received a first NOT by crisis quarter *t* ($\overline{NOT}_{gt}$) on the same controls as in equation (6)

$$\overline{NOT}_{gt} = \beta' \widehat{NB}_{gt} + \theta' LTV_{igpt} + \alpha'_{gp} + \delta'_{pt} + \varepsilon'_{igpt} \tag{7}$$

The second stage equation simply replaces $\widehat{NB}_{gt}$ in equation (6) with the predicted number of first NOT's

$$NOT_{igpt} = \tilde{\beta} \widehat{NOT}_{gt} + \tilde{\theta} LTV_{igpt} + \tilde{\alpha}_{gp} + \tilde{\delta}_{pt} + \tilde{\varepsilon}_{igpt} \tag{8}$$

Data and Sample

We use DataQuick Information Systems Inc. provided data on all home purchase transactions and all Notice of Trustee Sale recordings from the first quarter of 2001 through second quarter of 2010 collected from the San Diego County assessor's office. All home purchase transactions are recorded capturing the sale price and date, as well as information on both the primary and up to two subordinate the liens/mortgages securing the purchase; and an associated assessors file contains the address of the housing unit and the associated property attributes. California is an administrative/non-judicial foreclosure state, and a Notice of Trustee Sale (NOT) informs homeowners that their homes will be sold at a California public trustee foreclosure auction 21 days from the date of the recording of the notice in the county public record.

Housing price indices are created by estimating a hedonic model with quarter by year fixed effects for the entire sample period. The hedonic attributes include the age of the unit, lot size, the square footage of the housing unit, the number of bedrooms, the number of bathrooms, whether the unit is a condominium or coop within a larger structure, and whether the housing unit is a 2 to

4 family. Larger multifamily dwellings and non-Arm's length sales are excluded from the hedonic regression sample. Since our data ends in the second quarter of 2010, the 5 quarter moving average price index for the first and second quarter of 2010 are based on increasing the weight on the second quarter to 2 and 3, respectively, to replace the unavailable (at the time of data purchase) 3rd and 4th quarters of 2010.

For our sample of housing units/home purchase mortgages, we select a sample of single family housing units and associated home purchase mortgages that are likely the most at risk of experiencing negative equity during the housing market correction and foreclosure crisis. Specifically, we identify every single family housing unit transaction between the third quarter of 2001 and the second quarter of 2006 since housing units that had been held for longer than 5 years prior to the crisis had substantially more time to build up housing equity. If a housing unit was sold twice or more during this pre-crisis period, the most recent housing transaction is retained in the sample, and the earlier transactions are dropped. We also drop any mortgages that were issued a NOT prior to the third quarter of 2006 so that we can focus on the risk of foreclosure during the crisis period when housing prices were falling and equity was eroding. We also drop all non-Arm's length transactions because we do not have an accurate measure of the value for calculating a combined loan to value ratio. Our final sample of transactions contains 121,185 single-family housing units purchased during the pre-crisis period that did not receive a NOT during the pre-crisis period.

Finally, for the foreclosure regression sample, we create a panel with one observation per housing unit for every quarter between the third quarter of 2006 and the second quarter of 2010. A NOT dummy variable is created that is zero for every quarter starting in the third quarter of 2006 until the mortgage/housing unit has a first NOT recorded in the county assessor's office. The NOT variable is set to one in this first NOT quarter, and all further quarters are dropped from the sample for that housing unit. If a housing unit does not receive a NOT during the crisis period, all quarters are retained and the NOT variable is zero for those quarters. This data structure provides a linear probability equivalent to a proportional hazard model.[7]

Table 1 presents descriptive statistics for the regression sample. The first row is the dependent variable, which is 1 only when the first NOT is recorded in that quarter. The rate of first NOT is quite low at 0.0065 since it captures the flow of new NOT recordings. We measure foreclosure and negative equity at the census tract level using 2000 census tract definitions. The fraction NOT, which captures the share of pre-crisis transactions in a census tract that have received a first NOT between the onset of the crisis and the end of the current quarter, provides a better sense of the level of foreclosure during the crisis period, and the mean of this variable over all mortgages and quarters is 0.044 with a standard deviation of 0.050 suggesting sizable foreclosure rates and substantial variation across tracts in those rates. The average tract rates of negative equity are quite high at 0.40, with a high standard deviation across census tracts 0.25. The predicted values of tract negative equity moderately under predict the levels of the actual negative equity rates due to our use of the lower bound of the LTV bins, but they are highly correlated with the actual rates.

The Table also shows the means for the current combined LTV dummy variables, the transaction and mortgage attributes and the 2000 census tract attributes used in the regression models. During the sample period, 13% of mortgages have negative equity levels between 10 and 30 percent (LTV's between 1.1 and 1.3), while 15% have negative equity levels above 30 percent. Most of the transactions are sales of existing housing that was built more than two years ago, 65%

[7] Logit estimation using data formatted in this way is mathematically equivalent to the standard proportional hazard model.

of the principle mortgages are adjustable rate mortgages, and over 45% of the home purchase transactions include subordinate debt. These high rates of adjustable rate mortgages and subordinate debt are typical of California's high cost housing market, but less representative of the U.S. overall. Over 25 percent of mortgages had initial combined Loan to Value (LTV) ratios over 95 percent, but less than 3 percent had initial LTV's over 100. Using the 2000 census data, the typical share black or share households in poverty in a census tract is around 5 percent, while the average percent Hispanics is 21 percent.

Evidence on Identification

The model above is identified based on the timing of transactions up to the second quarter of 2006. The natural concern with this source of variation is that changes in the types of mortgages being issued in some tracts that experience increases in transaction volume could be different than the changes in the types of mortgages being issued in mortgages that have flat or decreasing transaction volume over time. Table 2 presents means for individual cohorts of loans separately for tracts that experienced low, medium and high increases in predicted negative equity, i.e. tracts with different patterns of transaction volume over time. Column 1 shows the bottom tercile of tracts on increases in predicted negative equity and column 3 shows the top tercile. Each panel shows the mean for a specific mortgage or housing unit attribute. The share of adjustable rate mortgages is increasing until the 05-06 cohort of mortgages (third quarter 05 through second quarter 06). The share of subordinate debt increases throughout the period, along with the share of loans with CLTV's greater than or equal to 95, but less than 100. The number of units sold that were less than two years old falls off dramatically in 04-05. However, these trends all appear in both the bottom and the top terciles by increases in tract negative equity during the crisis. Table 2 does not indicate any strong or systematic differences in the changes in the composition of loans between tracts that had large and small increases in the fraction of units in negative equity.

In Table 3, we provide a more formal test for this concern examining whether tracts exhibit short-run balance over transaction volume, which is the source of our identifying variation. Specifically, we create a dependent variable for tract-quarter relative transaction volume that is the number of arm's length transactions in a tract and quarter divided by the median number of quarterly arm's length transactions in the tract, and regress this variable upon the quarterly mean transaction and mortgage attributes for each tract. Unlike the models in equation (6) through (8) this variable only varies at the tract by purchase quarter and year. So, the model cannot include tract by purchase quarter and year fixed effects. Therefore, the regression includes tract by purchase year fixed effects and purchase quarter and year fixed effects. Consistent with balance over covariates, none of the individual coefficient estimates are statistically significant, and the F-statistic for the set of coefficients is only 0.74 and far from significance. Finally, the robustness of the magnitude of our estimated effects to the inclusion of these observable transaction attributes presented later in the paper provides further evidence of balance to support identification.

Finally, Table 4 shows that the instrument has power to explain both the actual levels of negative equity and the share of mortgages receiving initial foreclosure notices. The predicted negative equity variable has a coefficient estimate of 0.79 in the model for the actual share of units in negative equity consistent with a very strong relationship between predicted and actual levels of negative equity. We find a similarly strong and statistically significant relationship between predicted negative equity and the share of mortgages having received foreclosure notices or NOT's. A one standard deviation increase in predicted share in negative equity is associated with a 4.6 percentage point increase in rates of having received foreclosure notices relative to a base rate of 4.8 percent in our sample.

Results

Table 5 presents the reduced form first NOT model estimates for the predicted neighborhood negative equity measure plus the estimates on the current combined LTV dummy variables. The effect of tract levels of predicted negative equity on the likelihood of receiving a first NOT in a given quarter is substantial. A one standard deviation increase in predicted negative equity levels is associated with a 0.62 percentage point increase in the likelihood of receiving a first NOT relative to an average likelihood of 0.72 percent, or 86 percent of the average incidence. The magnitude of the estimated effect is very robust to the inclusion of initial mortgage attributes (increases by only three percent) even though the estimates on those controls are strong predictors of receiving a first NOT and dramatically erode (by approximately 50%) the magnitude of the estimates on the current LTV.

Table 6 presents the Two Stage Least Squares (2SLS) estimates, as well as the first stage estimates from the regression of fraction NOT on predicted levels of negative equity. The 2SLS effects of fraction mortgage having received an NOT are also highly significant and sizable. A one standard deviation increase in fraction NOT is associated with a 0.46 percentage point increase in the likelihood of any mortgage receiving a first NOT, about a 64 percent increase over the sample incidence of 0.72 percent. As in Table 4, the instrument is a powerful predictor of fraction NOT with an F-statistic of 42.[8] In fact, the coefficient on predicted negative equity is 40 percent larger in the transaction by crisis quarter sample as compared to the estimate from the tract by

[8] Kleibergen-Paap rk Wald F statistic allows for heteroskedastic and clustered errors. No formal critical values have been calculated for weak instruments outside of the iid case, and so Baum, Schaffer and Stillman (2007) recommend using the standard threshold of 10.

crisis quarter sample in Table 4. This large effect likely arises because the transaction sample places more weight on the tracts with more transactions where our predicted measure of negative equity more accurately captures actual levels of negative equity. As with the reduced form model, the magnitudes of these 2SLS estimates are very robust across models without and with the additional transaction and mortgage controls.[9]

Explaining the Increase in across Tract Dispersion

We further assess whether these estimated spillover effects can explain a substantial fraction of the large dispersion in foreclosure rates across neighborhoods that arose during the housing crisis. Table 7 presents the dispersion of key variables by crisis year. The standard deviation in the incidence of first NOT recordings rises from 0.0041 in the first year after the crisis to an annual maximum of 0.0110 between the 3rd quarter of 2008 and the 2nd quarter of 2009 (the year that housing prices reach bottom), or an increase in the dispersion of foreclosure by 0.0069. Turning first to the reduced form analysis, the standard deviation of the fraction of pre-crisis mortgages in negative equity rises from 0.0257 to 0.0641 during the same period. Multiplying the change in the standard deviation by the coefficient estimate on fraction in negative equity 0.031 from the first column of Table 5 yields 0.0012 implying that changes in the dispersion of negative equity can explain 17% of the increase in the standard deviation of first NOT recordings.

Turning to the 2SLS estimates, the increase in the standard deviation between 2006-07 and 2008-09 in fraction of units having ever received a NOT is 0.0484. The 2SLS estimate of the effect on the incidence of first NOT is 0.096. Multiplying the standard deviation change by the effect estimates imply an increase in the standard deviation of first NOT of 0.0046, or the increase

[9] Again with the addition of controls resulting in a small increase in the magnitude of the estimate of four percent.

in the dispersion of the stock of past mortgages having received a NOT can explain 67% of the 0.0069 change in the dispersion of the incidence of first NOT recordings.

Table 7 also shows that housing prices stabilized between 08-09 and 09-10 rising by 2 percent, and the incidence of new NOT recordings falls from 1.1 to 0.8 percent. However, the base level of total units having received foreclosure notices rise from 6.7 to 10.3 percentage points. Applying the estimated effect of the stock of foreclosures implies an increase in the incidence of new units receiving notices of approximately 0.4 percentage points. Therefore, while a naive comparison of the changes implies that the stabilization of housing prices led to only a modest change in the rate of new first foreclosure recordings of 0.3 percentage points, after accounting for neighborhood level spillovers the stabilization of housing prices may have led to a total 0.7 percentage point reduction in new recordings relative to the rate that would have occurred without stabilizing housing prices. Mortgage default decisions should rationally be based on expectations of future housing prices, and so stabilizing housing markets would be expected to have large effects on foreclosure rates and those expected reductions in new foreclosures may have been by delayed by spillovers effects from the existing stock of foreclosures.

Heterogeneity across Tracts

Panel 1 of Table 8 presents estimates for reduced form models where predicted negative equity is interacted with the tract share of residents who are black, who are Hispanic or the tract share of households in poverty. Panel 2 of Table 8 presents equivalent two stage least squares estimates where these interactions serve as instruments for interactions of fraction NOT with the same neighborhood attributes. The reduced form estimates suggest that the foreclosure spillover effects of negative equity are much larger in these disadvantaged neighborhoods with the differences primarily being driven by neighborhood share Hispanic. The average effect of negative equity from Table 5 is 0.62 percentage points relative to a base frequency of first NOT notices of 0.72. A one standard deviation change in percent Hispanic increases the effect by 0.14 percentage points. However, the two stage least squares estimates are relatively constant across different types of neighborhoods with small estimates on the interactions and level estimates that are comparable in magnitude to the estimates from Table 6. These results are consistent with negative equity levels being a stronger predictor of overall mortgage foreclosure (fraction NOT) in disadvantaged neighborhoods so that the larger reduced form estimates are deflated by a larger first stage. As a result, the estimated spillover effects of foreclosure are relatively stable across neighborhood types.

Robustness to Tract Trends

We can also extend the model to allow the time path of foreclosure in each neighborhood during the crisis to vary systematically with pre-determined neighborhood observables (Z_g).

$$NOT_{igpt} = \beta \widehat{NB}_{gt} + \theta LTV_{igpt} + \omega_t Z_g + \alpha_{gp} + \delta_{pt} + \varepsilon_{igpt} \tag{7}$$

These estimates are shown in Table 9. The inclusion of tract trends substantially reduces the reduced form estimates of the effects of predicted equity in panel 1, perhaps because bias from measurement error in our proxy is exacerbated by these additional controls. However, the two stage least squares estimates that address measurement error are very similar to the estimates without controls for trends on observables. The estimates from Table 6 are 0.096 and 0.100 without and with controls, while the estimates in Table 8 panel 2 are 0.098 and 0.092 without and with controls. However, we prefer the models without trends given the robustness of the estimates and the fact that the inclusion of trends weakens our instruments leading to a potential weak instruments problem.

Discussion

This paper provides the first quasi-experimental evidence of broad based neighborhood spillovers of foreclosures. While existing evidence documents highly localized foreclosure spillovers (often within 250 feet to ½ mile), no existing studies examine whether such localized and other broader spillover effects contribute substantially to extreme heterogeneity in neighborhood foreclosure rates observed during the crisis. We document substantial spillovers in foreclosure filings at the census tract level and the estimates are robust to including controls for transaction and mortgage attributes and allowing tracts to differ in the time path of foreclosures during the crisis based on pre-determined tract attributes. Further, these effects are broad based arising in both predominantly white, higher income neighborhoods and in neighborhoods with larger numbers of minorities or households in poverty.

Our estimated spillover effects can explain a substantial share of the increase in across neighborhood dispersion in foreclosure rates during the crisis, 17 percent of the increase for our reduced form estimates and conservatively 67 percent of the increase for our 2SLS estimates. Further, the stock of total housing units having experienced foreclosure continues to grow even as housing prices recover. Given the lag between housing price recovery and declines in the stock of foreclosures, these neighborhood spillover effects likely result in rates of new foreclosure filings that were far more persistent during the recovery than they would have been without the influence of neighborhood spillovers.

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Table 1. Analysis sample descriptive statistics

Variables	Description	Mean	Standard Deviation
Time Varying Neighborhood Variables			
First NOT	Received first Notice of Trustee Sale	0.0072	0.0847
Fraction NOT	Share pre-crisis sales having received first NOT	0.0421	0.0482
Negative Equity	Share of sales in negative equity	0.3975	0.2490
Pred Neg Equity	Share of sales predicted in negative equity	0.3272	0.1984
Housing Unit Negative Equity and Current Loan to Value Ratio			
Curr LTV 70-90	Current LTV between 0.7 and 0.9	0.2309	0.4214
Curr LTV 90-110	Current LTV between 0.9 and 1.1	0.2281	0.4196
Curr LTV 110-130	Current LTV between 1.1 and 1.3	0.1363	0.3431
Curr LTV 130-150	Current LTV between 1.3 and 1.5	0.0822	0.2747
Curr LTV > 150	Current LTV greater than 1.5	0.0692	0.2537
Transaction and Mortgage Attributees			
Arms length	whether the sale is an arm's length transaction	0.9347	0.2471
Less than 2 yrs old	whether the sale happens within two years after built	0.0774	0.2673
Adjustable Rate	whether the liens are adjustable rate mortgages	0.6361	0.4811
Subordinate debt	whether there are subordinate liens	0.4448	0.4969
Init LTV 80-95	80<Initial Combined LTV<=95	0.2582	0.4376
Init LTV 95-100	95<Initial Combined LTV<=100	0.2174	0.4125
Init LTV 100-110	100<Initial Combined LTV<=110	0.0109	0.1040
Init LTV > 110	Initial Combined LTV>110	0.0129	0.1127
Predetermined Neighborhood Variables (2000 Decennial Census)			
Share Black	Percent individuals who are black	5.2324	6.8493
Share Hispanic	Percent of individuals who are hispanic	20.9302	16.6945
Share Poverty	Percent households in poverty	5.6576	6.0118
Sample Size			
Home Sales	Number of pre-crisis sales	121185.0000	
Sales by Quarters	Number of quarterly NOT observations	1,870,680	

Notes: Means and standard devations are calculated for the full sample of crisis quarters by pre-crisis period home sales. Home sales are selected as most recent transaction on single family housing unit between third quarter 2001 and second quarter 2006 that did not have an NOT recorded between the transaction quarter and the second quarter of 2006. The sales by quarter sample is one observations per quarter beginning in the third quarter of 2006 and running until the recording of the first NOT or until the second quarter of 2010 when the data ends for every pre-crisis home sale.

Table 2. Initial loan attributes, by cohort and census tracts partitioned by predicted negative equity increases

	Census Tracts by Negative Equity Increases		
Loan Attributes	Low increase	Middle increase	High increase
Adjustable Rate			
Cohort 02-03	0.385	0.370	0.392
Cohort 03-04	0.636	0.646	0.666
Cohort 04-05	0.772	0.786	0.769
Cohort 05-06	0.688	0.704	0.692
Subordinate Debt			
Cohort 02-03	0.318	0.336	0.323
Cohort 03-04	0.415	0.468	0.440
Cohort 04-05	0.495	0.557	0.508
Cohort 05-06	0.517	0.602	0.530
Unit Less than 2 yrs old			
Cohort 02-03	0.139	0.047	0.149
Cohort 03-04	0.139	0.036	0.148
Cohort 04-05	0.054	0.011	0.044
Cohort 05-06	0.024	0.006	0.019
CLTV > 80			
Cohort 02-03	0.273	0.295	0.280
Cohort 03-04	0.280	0.276	0.264
Cohort 04-05	0.259	0.239	0.235
Cohort 05-06	0.241	0.216	0.213
CLTV > 95			
Cohort 02-03	0.126	0.200	0.178
Cohort 03-04	0.166	0.256	0.240
Cohort 04-05	0.239	0.342	0.288
Cohort 05-06	0.275	0.374	0.305
CLTV > 100			
Cohort 02-03	0.016	0.030	0.029
Cohort 03-04	0.011	0.016	0.016
Cohort 04-05	0.006	0.009	0.011
Cohort 05-06	0.015	0.011	0.010
CLTV > 110			
Cohort 02-03	0.022	0.021	0.024
Cohort 03-04	0.015	0.012	0.017
Cohort 04-05	0.012	0.009	0.011
Cohort 05-06	0.011	0.032	0.012

Notes: The table presents the fraction of transactions in each origination cohort that have the above attribute measures separately for three terciles of census tracts: those tracts having the lowest, middle and highest levels of increase in the predicted share of units in negative equity between the third quarter of 2006 and the second quarter of 2010.

Table 3. Relative Transaction Volume and Average Loan Attributes

Variables	Estimates
Adjustable Rate	-0.0788195
	(0.059)
Subordinate Debt	0.0382195
	(0.061)
Unit Less than 2 yrs old	0.1633821
	(0.190)
CLTV > 80	-0.0589384
	(0.063)
CLTV > 95	-0.0564049
	(0.079)
CLTV > 100	0.5078718
	(0.550)
CLTV > 110	0.1705669
	(0.201)
Observations	8,708
F-Test	0.74 [0.638]
R-squared	0.463

Notes: The Table presents the estimates for a model of the number of mortgage originations in each tract and purchase quarter as a fraction of the median number of quarterly transactions for that tract. The controls are measured as the fraction of mortgages in a tract and purchase quarter that have this attribute. The sample contains all tract by purchase quarter combinations with a positive number of transactions. The model conditions on tract by purchase year and purchase year by quarter fixed effects. The F-test is intended to detect whether variation in tract mortgage volume over time can be explained by variation in the composition of the mortgages being originated.

Table 4. Predictiveness of Negative Equity Instrument

	Share in Negative Equity	Fraction NOT
Predicted Negative Equity	0.791***	0.230***
	(0.149)	(0.064)
Observations	9,376	9,376
R-squared	0.963	0.767

Notes: The table presents estimates of tract share of units in negative equity and fraction of units having received a first NOT on the predicted level of negative equity in a sample of tract by crisis quarter and year. The model contains tract and crisis quarter by year fixed effects.

Table 5. Reduced Form Effects of Negative Equity

Variables	Estimates	
	w/ out controls	w/ controls
Predicted Negative Equity	0.031***	0.032***
	(0.006)	(0.006)
Current LTV 70-90	0.0006***	-0.0007***
	(0.000)	(0.000)
Current LTV 90-110	0.003***	-0.0005*
	(0.000)	(0.000)
Current LTV 110-130	0.007***	0.003***
	(0.001)	(0.001)
Current LTV 130-150	0.012***	0.006***
	(0.001)	(0.001)
Current LTV > 150	0.017***	0.009***
	(0.001)	(0.001)
Observations	1,748,520	1,748,520
R-squared	0.015	0.015

Notes: The table presents estimates of a model for a housing unit receiving a first NOT in a specific quarter regressed on predicted fraction of mortgages in the census tract in negative equity. The model controls for tract by purchase quarter fixed effects and crisis quarter by purchase quarter fixed effects. The w/ controls column adds the transaction and mortgage variables from Table 1. Standard errors are clustered at the tract level.

Table 6 Spillover Effects of Foreclosure

Two Stage Least Squares Model of First NOT		
	w/ out controls	w/ controls
Fraction NOT	0.096***	0.100***
	(0.009)	(0.009)
First Stage Model of Fraction NOT		
	w/ out controls	w/ controls
Predicted Negative Equity	0.324***	0.323***
	(0.050)	(0.050)
First Stage F-Stat	41.96	42.21
Observations	1,748,520	1,748,520
First Stage R-squared	0.791	0.793
Second Stage R-squared	0.015	0.016

Notes: The Table presents two stage least squares estimates for whether a pre-crisis home sale has a first NOT in a specific crisis quarter as a function of the fraction of pre-crisis sales receiving a first NOT between the third quarter of 2006 and the current quarter (Fraction NOT). The fraction NOT is instrumented using the predicted share of mortgages in negative equity in each purchase quarter. The model controls for census tract by purchase quarter fixed effects and crisis quarter by purchase quarter fixed effects. Panel 1 presents the two stage least squares estimates and panel 2 presents the estimates for the first stage. The w/ controls specification includes the transaction and mortgage attributes from Table 1. Standard errors are clustered at the census tract level.

Table 7 Crisis Year Means and Standard Deviations

Crisis Year	County Price Index	First NOT	Fraction NOT	Pred Neg Equity
Year 06-07	4.733	0.0024	0.0040	0.0892
	(0.000)	(0.0041)	(0.0059)	(0.0257)
Year 07-08	3.994	0.0076	0.0256	0.2615
	(0.003)	(0.0071)	(0.0236)	(0.0468)
Year 08-09	2.970	0.0106	0.0669	0.5410
	(0.002)	(0.0110)	(0.0543)	(0.0641)
Year 09-10	3.037	0.0083	0.1033	0.5195
	(0.001)	(0.0062)	(0.0724)	(0.0648)

Notes: Table presents the means and standard deviations in paratheses of tract year averages across all transactions from the third quarter of one year to the second quarter of the next. The standard deviation is show in parentheses.

Table 8 Heterogeneous Effects of Negative Equity and Spillovers

	Reduced Form Estimates			
	Percent Black	Percent Hispanic	Percent Poverty	All Interactions
Predicted Negative Equity	0.026***	-0.000	0.021***	0.001
	(0.006)	(0.005)	(0.006)	(0.004)
Pred Neg Equity*Share Black	0.046***			0.019***
	(0.007)			(0.006)
Pred Neg Equity*Share Hispanic		0.046***		0.049***
		(0.003)		(0.004)
Pred Neg Equity*Share Poverty			0.071***	-0.021**
			(0.009)	(0.010)
Observations	1,748,520	1,748,520	1,748,520	1,748,520
R-squared	0.015	0.015	0.015	0.015

	Two Stage Least Squares Estimates			
	Percent Black	Percent Hispanic	Percent Poverty	All Interactions
Fraction NOT	0.105***	0.096***	0.098***	0.101***
	(0.011)	(0.032)	(0.013)	(0.037)
Fr NOT*Percent Black	-0.060*			-0.060
	(0.031)			(0.050)
Fr NOT*Percent Hispanic		0.007		0.002
		(0.044)		(0.055)
Fr NOT*Percent Poverty			0.013	0.023
			(0.041)	(0.048)
First Stage F-Stat	19.34	4.46	10.91	2.40
Observations	1,748,520	1,748,520	1,748,520	1,748,520
R-squared	0.016	0.016	0.016	0.016

Notes. The Table presents the reduced form and two stage least squares estimates for whether a pre-crisis home sale has a first NOT in a specific crisis quarter as a function of the fraction of pre-crisis sales receiving a first NOT between the third quarter of 2006 and the current quarter (Fraction NOT) and this variable interacted with pre-determined tract attributes. In the two stage least squares estimates, the fraction NOT and its interactions are instrumented using the predicted share of mortgages in negative equity in each purchase quarter and that share interacted with the tract attributes. The model controls for census tract by purchase quarter fixed effects and crisis quarter by purchase quarter fixed effects. Panel 1 presents the reduced form estimates and panel 2 presents the estimates for the two stage least squares estimates. Standard errors are clustered at the census tract level.

Table 9 Controlling for Tract Specific Foreclosure Trends

Reduced Form Model of First NOT		
	w/ out controls	w/ controls
Predicted Negative Equity	0.009**	0.008**
	(0.004)	(0.004)
Observations	1,748,520	1,748,520
R-squared	0.015	0.016
Two Stage Least Squares Model of First NOT		
	w/ out controls	w/ controls
Fraction NOT	0.098***	0.092***
	(0.031)	(0.029)
First Stage Model of Fraction NOT		
	w/ out controls	w/ controls
Predicted Negative Equity	0.092***	0.092***
	(0.031)	(0.030)
First Stage F-Stat	9.04	9.20
Observations	1,748,520	1,748,520
First Stage R-squared	0.901	0.901
Second Stage R-squared	0.015	0.016

Notes: The Table presents reduced form two stage least squares estimates for whether a pre-crisis home sale has a first NOT in a specific crisis quarter as a function of the fraction of pre-crisis sales receiving a first NOT between the third quarter of 2006 and the current quarter (Fraction NOT). The fraction NOT is instrumented using the predicted share of mortgages in negative equity in each purchase quarter. The model controls for census tract by purchase quarter fixed effects and crisis quarter by purchase quarter fixed effects plus the interaction of pre-determined tract attributes with current year fixed effects. Panel 1 presents the reduced form estimates, panel 2presents the two stage least squares estimates and panel 3 presents the estimates for the first stage. The w/ controls specification includes the transaction and mortgage attributes from Table 1. Standard errors are clustered at the census tract level.