Property Value Impacts of Foreclosed Housing Acquisitions Using a Markov Model

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Abstract:

Community-based organizations (CBO) across the country are working to stabilize neighborhoods affected by the recent foreclosure crisis through acquisition and redevelopment of foreclosed properties. One rationale for this work is the alleviation or avoidance of negative impacts associated with foreclosures, including lost value to proximate properties. In this paper, we estimate the lost value to proximate properties associated with a single foreclosure using a Markov model of transitions between various states associated with the foreclosure process. We apply our model to a case study of candidate foreclosure properties identified by a CBO in Chelsea, MA. Our model produces a rank ordering of these foreclosures by their expected proximate property value impacts, which the CBO can use to identify and evaluate acquisition candidates. We conclude by discussing the limitations and possible extensions of this model for use by other CBOs working to stem the tide of negative foreclosure impacts in their communities.

Keywords:

foreclosed housing, Markov chains, cost-benefit analysis, decision models

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1. Introduction

After experiencing the longest sustained boom on record, the U.S. housing market finally peaked in 2006. The fall in house prices that followed the boom was both a consequence of and a catalyst to rising defaults on residential mortgages. Initially, defaults were concentrated among subprime and high-risk loans that had been made near the peak of the market, often with discounted terms or incentives that expired a few years into the loan. Borrowers with these loans saw their mortgage costs rise significantly, but were unable to sell out of the loan because of stagnating prices. The rash of foreclosures that quickly followed created a vicious cycle of abandoned properties, which lowered the values on other homes nearby and put additional borrowers underwater on their mortgages (i.e. owing more than the property was worth). These effects were further exacerbated by the broader economic recession and rising unemployment, leading borrowers with prime and low-risk mortgages to also fall into default and eventually foreclosure. Indeed, according to one estimate nearly 8 million homes entered the foreclosure process in 2007-2010 (Joint Center for Housing Studies, 2011), affecting families and communities across the country.

Among the many negative externalities associated with high foreclosure rates, neighborhood destabilization has perhaps the widest reaching effects. The presence of even a single foreclosure has been linked to decreased values on neighboring properties, increased crime and social disorder, higher vacancy rates, and loss of social cohesion (see, e.g. Kingsley et al, 2009). In neighborhoods with multiple foreclosures, these effects are even more severe (Schuetz et al, 2008). In the face of these potential outcomes, many non-profit community-based organizations (CBOs) have sought to purchase foreclosed properties to stem the spillover effects on surrounding neighborhoods. Acquiring and redeveloping foreclosures not only improves the quality of the overall housing stock, but can also provide affordable rental and homeownership opportunities to increase residential stability and neighborhood investment (Mallach, 2009). Resource constraints, however, often limit the number of foreclosed properties that a CBO can acquire; strategically choosing properties that can maximize neighborhood revitalization efforts is thus vital to successful achievement of CBOs' missions.

New work on community-based and public-sector applications of operations research has recently begun to address and include social impact factors such as these into decision models (e.g. Johnson, 2011). As these analyses demonstrate, there are a number of ways to measure social impacts in this context, such as using proxies based on readily observable and quantifiable outcome variables. In the case of foreclosed housing impacts, a common proxy for social impacts has been changes in sales prices on properties proximate to a foreclosure (Harding et al, 2009; Campbell et al, 2010, Whitaker and Fitzpatrick, 2011). This approach follows convention from the real estate economics literature, which assumes that neighborhood characteristics and dynamics relevant to residents are capitalized in property values (Li & Brown, 1980). The following analysis adopts this method of evaluating social impacts, and applies decision models to assist CBOs in their neighborhood stabilization and foreclosure mitigation activities. It uses a Markov chain to estimate probabilistic outcomes for a set of foreclosed properties, which are then combined with findings from prior research on the impacts of foreclosures on proximate properties. The result is a property value impacts (PVI) model that can be used to evaluate different foreclosed properties considered for acquisition and redevelopment by a CBO.

This paper begins with a review of prior research on the social impacts of foreclosures and attempts to quantify these effects. It then discusses the theory and assumptions underlying the model developed to compare such effects for the benefit of CBO foreclosure acquisitions. After specifying a Markov chain of possible foreclosure stage transitions, the paper introduces the PVI model to estimate the effect of a foreclosure the surrounding neighborhood, using the appraised values of all proximate properties as a proxy for expected social impacts. The PVI model is then run on a case study of foreclosure candidates identified by a CBO operating in Chelsea, MA, with sensitivity tests conducted on the results. Finally, the paper discusses the implications of these findings for foreclosure policy and practice, and mentions possible further research opportunities for decision sciences on this topic.

2. **Social Impacts of Foreclosed Housing**

As noted in a review of foreclosure impact studies conducted by Kingsley et al (2009), observing and quantifying the myriad effects on individuals, communities, and housing markets from foreclosures is both methodologically and financially impractical. Still, as testament to the scope and severity of the ongoing foreclosure crisis, several recent studies have attempted to do just that, using various measures and proxies for unobservable outcomes. This section reviews some of this literature and identifies plausible ways to evaluate social impacts for use in CBO foreclosure acquisition decision models.

The impact of a foreclosure on the individuals living in the foreclosed unit can be severe, ranging from displacement and housing instability, to financial insecurity and economic hardship, increases in personal and family stress, and poorer health outcomes (Kingsley et al, 2009). These effects can also have long lasting consequences, such as impaired credit and subsequent defaults on other consumer loans (Brevoort & Cooper, 2010), poorer mental and physical health outcomes (Bennett et al, 2009), and poorer school performance (Been et al, 2011). Indeed, individuals do not even have to own property to be impacted by foreclosures, as evidenced by the many tenants displaced from their rental units when their landlords failed to make mortgage payments (Been & Glashausser, 2009).

In addition to their impacts on individuals, foreclosures often have a significant impact on the surrounding neighborhood, particularly in dense urban areas and/or when multiple foreclosures occur within close proximity to each other. These effects can be separated into those that impact the social and community life of the neighborhood, and those that are experienced through changes in the market for housing in that neighborhood. Social effects include increases in crime, residential turnover, and blight, all of which contribute to decreases in neighborhood image and resident quality of life (Immergluk & Smith, 2006; Shlay & Whitman, 2006; Schuetz et al, 2008; Li & Morrow-Jones, 2010). Market effects, meanwhile, include declines in neighborhood property values, sales, and residential investment (Collins, 2008; Harding et al, 2009; Lin et al, 2009; Whitaker and Fitzpatrick, 2011). Of these, the effect most commonly studied has been neighborhood property values, which are often seen as a proxy for other social and economic impacts (Schuetz et al, 2008; Frame, 2010).

Lee (2008) identifies three ways in which foreclosures impact neighboring property values. First, decreased maintenance and neglect of foreclosed properties reduces incentives for owners of neighboring properties to continue upkeep of their homes, due to the visual perception of a neighborhood on the decline. Second, the depressed selling prices of foreclosed properties skew the median house price within a neighborhood and show up in assessments of neighborhood ‘comparables’ by real estate agents (Frame, 2010). Finally, large numbers of foreclosures can significantly increase the supply of properties on the market at any given time, which places downward pressure on the selling prices of proximate properties.

While the spate of recent studies on foreclosure impacts to proximate property values vary in their geographic and temporal scopes, some consensus has nonetheless emerged on the magnitude of such effects, which are estimated to be around 1-2% of the value of properties within a short distance (no more than 1,000 feet) from the foreclosure. These studies, including Immergluk and Smith (2006), Leonard and Murdoch (2009), Rogers and Winter (2009), Campbell et al (2009), and Wassmer (2010), generally use hedonic regression analyses of house prices to control for a number of property and neighborhood-specific characteristics and isolate the foreclosure effect (see Miller et al (2009) and Frame (2010) for summaries of these studies).

Some studies of foreclosure effects provide more nuanced findings relating to specific features of neighborhoods, foreclosed units, or the surrounding market. For example, Harding et al (2009) estimate different effects on sales prices of non-distressed properties based on what stage of the foreclosure process a nearby property was in (i.e. pre-foreclosure, pre-auction, or REO), and find that REO properties have generally greater effects, as more time in the foreclosure process leads to increased deterioration or risk of vandalism to a foreclosed property. Immergluk (2010) and Lin et al (2009) estimate different effects in urban/suburban and weak/strong property markets, and find greater impacts occurring in the former categories. Hartley (2010) further disaggregates the effects on different markets by the mechanisms through which property values are impacted, namely the effect of increased supply from competing for-sale foreclosed properties versus the disamenities of foreclosed and abandoned properties; in stronger markets the former has more of an impact, while weaker markets are more affected by the latter. A few studies assess the impact of multiple foreclosures in an area, including Schuetz et al (2008) and Harding et al. (2009), and find the number of proximate foreclosures in the area generally multiplies the effects on neighboring prices. Recent research indicates that the added effect of vacancies and tax delinquencies increases property value losses on transacting properties as compared to foreclosures alone, and that the magnitude of these impacts is higher than previously estimated (Whitaker and Fitzpatrick, 2011).

Common to all these prior studies is the single non-distressed property as the unit of analysis, evaluated at the time of a transaction at which its sales price can be observed. By observing only those proximate properties that are transacting, however, such analyses have not considered the effect on proximate properties that were not transacting during the foreclosure of a nearby property. The only known study to estimate the impact of foreclosures on all proximate properties was conducted by the Center for Responsible Lending (2009), which used discount factors calculated by Harding et al (2009) to extrapolate the effect of foreclosures on surrounding property values across the country. They conservatively estimate that in 2009 alone nearly 70 million households lost over $500 million in wealth due to declines in neighboring property values from the foreclosure crisis. While this estimate provides some context for the scope of the possible spillover effects from foreclosures nationally, it does not isolate that effect by state or metro area, much less at an individual property level. Indeed, no prior research we know of has sought to model the effect of a single foreclosure on all proximate property values.

3. Theory of Property Value Impacts from Foreclosed Housing

Exposure to a foreclosure results in a number of negative externalities, such as increased blight, crime, and social disorder, that are assumed capitalized in the property values of proximate properties. The impact of a foreclosure on proximate property values is similar to that of a radiation source polluting the surrounding area, in that the distance between the source and an infected agent, as well as the duration of and time since exposure to the radiation, determine the magnitude of the effect. Properties close to a foreclosure in the later stages of the foreclosure process, therefore, will experience a greater percentage loss relative to properties further away from early-stage foreclosures.

As the prior research on proximate property value impacts from foreclosed housing demonstrate, hedonic analyses are an appropriate and common approach for untangling discrete effects on housing outcomes. Hedonic analyses view a given dependent variable on a good (e.g. unit cost) as a function of a set of characteristics specific to the good, which are regressed against the dependent variable to determine the magnitude and direction of each identified factor (Rosen, 1974). Such equations are especially useful for evaluating supplies of heterogeneous goods, such as housing, in which differences in a range of characteristics (e.g. of the property, structure, location, and market conditions) combine to determine the output price (Malpezzi, 2002). For example, Malpezzi (2002) specifies a log-linear form of a generalized hedonic regression for housing costs, using imputed rents as the dependent variable, which is expressed as:

$$\ln R = \beta_0 + S\beta_1 + N\beta_2 + L\beta_3 + C\beta_4 + \varepsilon \tag{1}$$

where ln R is the natural log of imputed housing rents, S, N, L, and C are sets of structural, neighborhood, locational, and contract characteristics of the property, respectively, the β_i are the regression coefficients, and ε is the error term.

Our PVI model assumes a hedonic equation of property values that is a function of, among other things, the presence of a proximate foreclosure. This assumption is also used in other analyses of property value impacts from foreclosures (Campbell et al, 2009; Leonard & Murdoch, 2009). We further assume that other features of proximate properties are held constant in the short term, so that the presence of a foreclosure is the only factor to changes in property values; variations in the starting values of the properties themselves are thus not relevant to this analysis.

Prior literature on the effects of foreclosed properties has relied on observed sales prices of non-distressed properties that are proximate to properties in some stage of the foreclosure process (Harding et al, 2009; Campbell et al, 2009). By observing only those proximate properties that are transacting, however, such analyses have not considered the effect on proximate properties that were not transacting during the foreclosure of a nearby property. The PVI model, in contrast, considers the aggregate impact of a single foreclosure on all proximate properties. We assume such impacts to be linearly additive across proximate properties, and that any possible second-order effects from the proximate foreclosure are already factored into the percentage discount applicable to a proximate property value. This suggests that for a given property h_1 proximate to foreclosed property p, the associated value discount factor y_1 already includes any possible second-order effects on h_1 that may result from the effect of p on h_2 (see Figure 1).

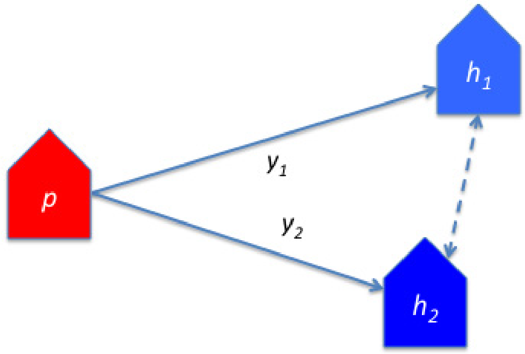


Figure 1: Model of Propagation of Foreclosure Impacts upon Property Value

Second-order effects could occur, for example, if the presence of foreclosed property p induces the owner of h_2 to reduce the amount of maintenance he does on his home, which in turn lowers the value of h_1. We assume in the PVI model, however, that the discount factor y_1 already captures any decline in the value of h_1 that results from the lower quality of h_2, in addition to the direct effect of p.

The PVI model also does not account for differences across neighborhoods with different degrees of real estate market strength in the aggregation of impacts across proximate properties, though there is some evidence to suggest that foreclosure impacts are greater in weaker markets (Lin et al, 2009). It is possible, therefore, that the property value impacts estimated by the PVI model would have a less than additive effect in stronger real estate markets, where housing demand is not greatly harmed by the presence of foreclosures and their neighborhood effects. Similarly, foreclosures in a weaker housing market may have a greater than additive effect on proximate property values, particularly in neighborhoods with underlying social or market issues (e.g. high crime rates, presence of local disamenities to residents) where residential stability and housing demand are already low. Calculating such differences, however, is beyond the scope of the PVI model developed here.

This additive assumption in the PVI model raises the question of whether the density and distribution of properties proximate to a foreclosure influences its property value impact. We assume they do not; referring to the radiation analogy described above, the magnitude of impacts on a proximate property is not affected by the presence or absence of other properties to absorb the detrimental effects from a foreclosure. Furthermore, for analyses that compare properties residing in the same neighborhood (i.e. with relatively constant density levels), such variations are likely to be minimal.

4. Markov Chain of Foreclosure Stage Transitions

One finding of prior research on the proximate property value impacts associated with foreclosures is that such effects vary with the stage of the foreclosure process (Harding et al, 2009). A CBO considering possible acquisition opportunities would need to know, therefore, in what stage of the foreclosure process candidate properties are likely to be at some point in the future to estimate relative foregone lost property value impacts realized at that time. Such future conditions cannot be predicted with certainty; we can, however, use a Markov chain to estimate the probability that a candidate property will be in a certain stage of the foreclosure process, given its current stage, and adjust expected lost value impacts accordingly.

Markov chains are mathematical representations of stochastic processes that have a finite and countable set of possible values that can be achieved. As described by Ross (2009), such chains provide a probability distribution of future states conditioned on an observed current state. This distribution is summarized by a transition matrix $\boldsymbol{P}$, with each entry p_{ij} representing the probability that a process in state i at time t will be in state j at time $t+1$. The matrix $\boldsymbol{P}^n$ represents such probabilities at some n-periods in the future, and is given by the Chapman-Kolmogorov equations as the nth product of $\boldsymbol{P}$, or $\boldsymbol{P}^n = \underbrace{P \cdot P \cdots P}_{\text{n – 1 times}}$.

Markov chains assume stationary and time-invariant probabilities of future states, which are independent of the order of states achieved. They are also assumed to be irreducible (all states communicate with each other) and ergodic (all states are positive recurrent and aperiodic). This matrix further assumes that a property can only occupy one state per period, and that the length of the period can vary by state.

The transition matrix of stages in the foreclosure process developed for the PVI model is consistent with these assumptions; properties evaluated for this analysis can move between states in any given period and do so with positive probabilities given by data on actual loan performance (described more fully below). Thus we can compute the long-term proportion of time that p will be in state i as the values π_j, $j \in S_p$, that solve the equation:

$$\pi_i = \sum_{j \in S_p} \pi_j \cdot P_{ij} \quad \forall i \in S_p \tag{2}$$

Markov chains have been used in some prior analyses of real estate outcomes, such as to model whether real estate returns can be predicted by past performance (Lee & Ward, 2001), track trends in rental vacancy rates (Guasch & Marshall, 1985) or evaluate real estate-backed financial products (Zipkin, 1993). With respect to residential foreclosures, a recent body of literature is emerging that also uses Markov chains, for example, in models of the default decisions of individual households (Corbae & Quintin, 2009), default probabilities applied to expected loan account balances (Grimshaw & Alexander, 2011), and non-default durations of loans for portfolio management (Hassan et al, 2010). The Markov chain developed for this paper resembles those used in these prior analyses; to our knowledge, however, this paper is the first to use a Markov chain of foreclosure states to model potential property acquisition opportunities.

5. The Property Value Impacts (PVI) Model

We turn now to the development of the PVI model of expected impacts on proximate property values from a single foreclosure. Our model specification assumes the following definitions for all relevant variables:

<u>Foreclosure Stages:</u>

C = current on mortgage, either through a refinance or payments by the original owner, or through a sale of the property to a new owner;

DQ = delinquent, i.e. mortgage payment is 30 to 89 days past due;

DF = mortgage in default after payment is 90+ days past due, but before foreclosure proceedings have started;

FC = in foreclosure, i.e. after a foreclosure filing is made by the lender but before a foreclosure auction. Massachusetts law requires at least a 3 week period of notice between the filing and auction, during which time the owner can still become current on the loan and retain the property;

REO = real estate owned, i.e. when the property reverts to the lender if there are no buyers at auction and the original owner has not become current on the loan. The property stays in REO until the lender either resells to another buyer (which returns the property to current status) or decides to land bank the property for future use.

Indices and Sets:

p = a distressed candidate property for acquisition, i.e. in state *DQ, DF, FC*, or *REO*;

s_p = current state of property p; S_p = set of all possible states for property $p = \{s_p\}$;

$i, j \in S_p$ = discrete states for p at a given point in time;

h = a particular property (distressed or non-distressed) proximate to distressed property p;

H = set of all properties in proximity to distressed property $p = \{h\}$;

Parameters:

P^n_{ij} = the probability that distressed property p, currently in state i, will be in state j n-periods from now; $P^1_{ij} \equiv P_{ij}$

π_j = the long-term proportion of time distressed property p is in state j;

v_h = current value of property h;

d_{ph} = the distance between distressed property p and property h;

D^{max} = the maximum distance a property $h \in H$ can be from p;

$y_{ph}(i,d)$ = percent discount on value of property h that is distance d from distressed property p known to be in foreclosure state i currently;

I = market interest rate used to calculate present value of property value impacts some number of periods in the future

Using these definitions, we let $L_{ph}(i,d)$ be the estimated appraised value loss in the next period to a property h at a distance d from distressed property p that is known to be in foreclosure state i in the current period, and calculate it as:

$$L_{ph}(i,d) = v_h \cdot y_{ph}(i,d) \tag{3}$$

Of course, we don't know with certainty the foreclosure state of property p one period from now. We thus compute the next period's property value loss in expectation as:

$$E[L_{ph}(i,d)] = v_h \cdot \left(\sum_{k \in S_p} y_{ph}(k,d) \cdot P_{ik} \right) \qquad (4)$$

where P_{ik} is the probability that distressed property p currently in foreclosure stage i will be in foreclosure state k next period, as determined by the transition matrix $\boldsymbol{P}$ described above.

The total expected property value lost by property h that is distance d from distressed property p should account for a time horizon T over which property p could transition into multiple states between beginning stage i and an ending state. For any $t \leq T$, let $L^t_{ph}(i,d)$ equal the expected property value impacts $t \in T$ periods in the future on property h that is a distance d to distressed property p known to be in foreclosure state i currently. We then compute this expected t-period property value impact as:

$$L^t_{ph}(i,d) = v_h \cdot \left(\sum_{k \in S_p} y_{ph}(k,d) \cdot P^t_{ik} \right) \qquad (4')$$

where P^t_{ik} is the t-period transition probability between states i and k, derived from the t-period transition matrix P^t.

The expected present value of property value impacts should account for the time value of money via an interest rate of I per period. We let $NL^t_{ph}(i,d)$ be the present value of the expected lost property value impacts over a t-period timeframe on a property h that is a distance d from distressed property p known to be in foreclosure state i, which we calculate as:

$$NL^t_{ph}(i,d) = \frac{L^t_{ph}(i,d)}{(1+I)^t} \qquad (5)$$

As described in section 4 above, we assume such impacts to occur additively across all affected proximate properties; thus we define $NL^t_p(i)$ as the total expected value lost on a set of properties H that are proximate to distressed property p in foreclosure state i currently, and calculate it as:

$$NL^t_p(i) = \sum_{h \in H | d_{ph} \leq D^{\max}} NL^t_{ph}(i,d) \qquad (6)$$

Thus for every candidate foreclosed property p, we estimate its associated expected present value of total proximate property value losses some t-periods into the future, as a proxy for the larger set of possible neighborhood impacts that might contribute to neighborhood destabilization. We now apply the PVI model to a case study of such properties.

6. Case Study: Chelsea, MA

Data and Model Specifications

Our data on candidate properties for the PVI models come from a CBO operating in Chelsea, MA that has been recognized as a leader and innovator in non-profit foreclosure acquisition and redevelopment for neighborhood stabilization (NeighborWorks, 2009). Chelsea is a small urban community and former industrial hub adjacent to and north of Boston, MA, with one of the more diverse and impoverished populations in the greater Boston area (U.S. Census Bureau, 2009). It is also one of the communities in Massachusetts hardest hit by the foreclosure crisis, with foreclosure rates consistently in the top ten among all municipalities in the Commonwealth (Massachusetts Housing Partnership, 2010). It is within this context that our partner CBO began to acquire properties for neighborhood stabilization in 2008.

For our application of the PVI model, we selected a set of 35 residential properties that were in some stage of the foreclosure process and identified as candidates for potential acquisition and redevelopment by our partner CBO in Chelsea as of October 2009. Table 1 presents some summary statistics on these properties.

Statistic	**Number of properties within 500ft**	**Aggregate value of proximate properties**	**Average value of proximate properties**	**Number of other candidate properties within 500ft**
Minimum	104	$32,608,600	$284,683	0
Maximum	193	$69,927,200	$497,653	11
Mean	150.2	$52,571,511	$350,386	5.9
25th Percentile	127	$41,024,100	$319,669	3
Median	155	$55,297,100	$350,592	6
75th Percentile	174.5	$61,653,500	$372,878	9

Table 1: Summary Statistics on Candidate Foreclosed Properties

The foreclosed property addresses were geocoded and matched to parcel-level boundary files accessed through MassGIS, a state-provided GIS data repository. From this data, we determined the distances from each candidate property within the CBO service area to all proximate properties up to 500 feet away (see Figure 2). This distance is appropriate based on findings from Harding et al (2009) that the impacts on non-distressed properties from a foreclosed unit more than 500 feet away were not statistically significant.

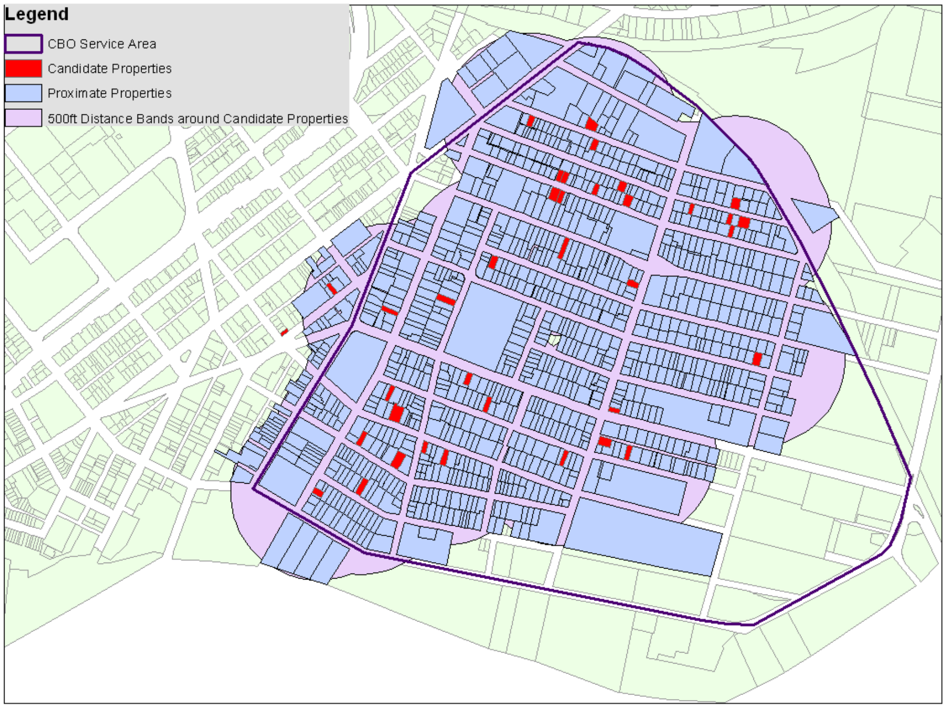


Figure 2: Candidate and Proximate Properties

Data on proximate property values were culled from state tax assessment records. Using appraised values has two primary advantages over recent sales price data used in prior property value impact analyses; appraised values are readily available from public records, and are appropriate to assess the impact on all properties proximate to a foreclosure, since not all such properties will have had a recent transaction from which to observe a market price.

To populate the Markov transition matrix used in the PVI model, we used data provided by the Federal Reserve Bank of Boston on all residential loans in Chelsea that were active during 2010[1]. This data linked monthly records of the foreclosure status of each loan, which allowed for calculations of the number and share of loans that transitioned from one stage to the next in each period. The transition matrix produced by this data is shown in Table 2:

[1] The Boston Fed database used information from Lender Processing Services (LPS) and the Warren Group on the status of all loans on a monthly basis. While some properties may have multiple loans associated with them, we assume the transition rates calculated are representative of properties with a single loan.

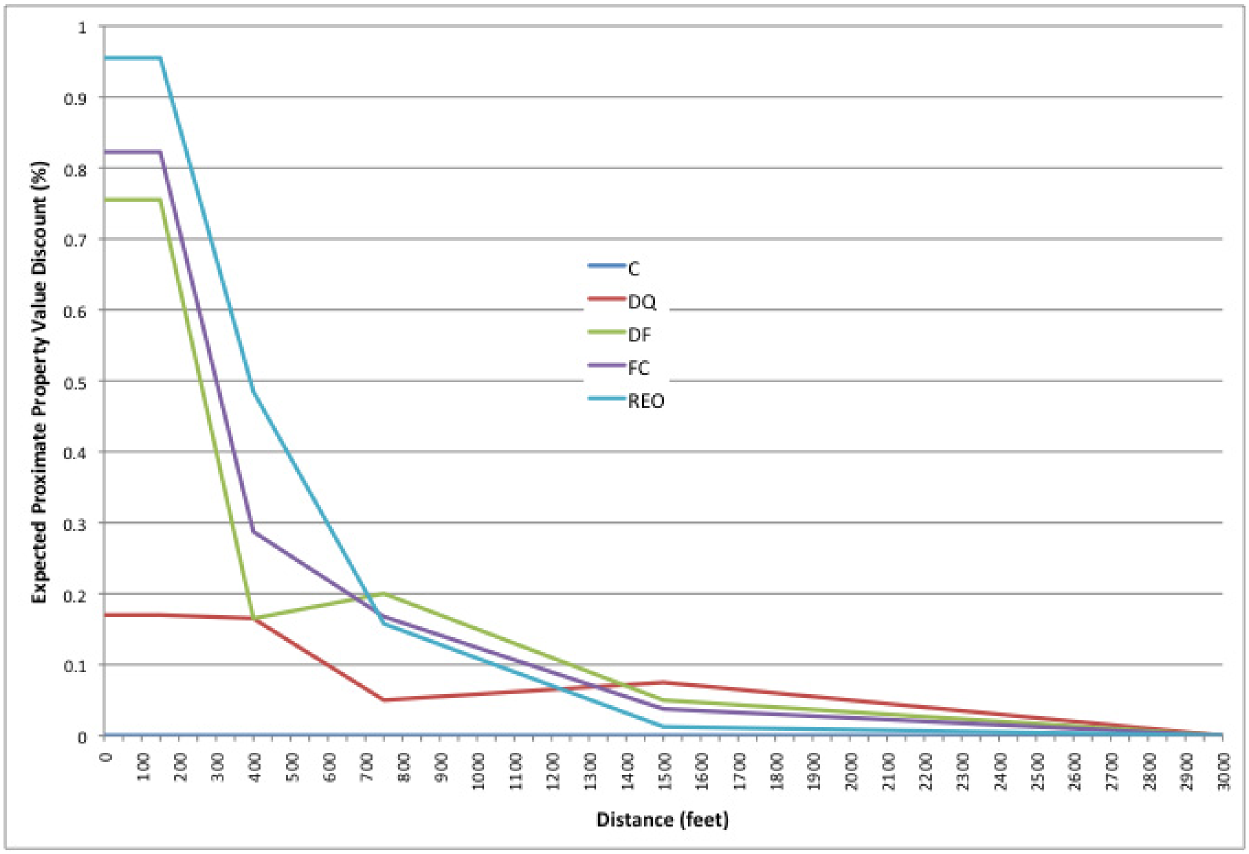
	Status at time *t*+1				
Status at time *t*	**C**	**DQ**	**DF**	**F**	**R**
C	0.870	0.130	0.000	0.000	0.000
DQ	0.047	0.105	0.762	0.084	0.003
DF	0.042	0.028	0.828	0.101	0.002
F	0.040	0.000	0.048	0.869	0.043
R	0.070	0.000	0.000	0.000	0.930

Note: See Appendix A for more detail on this data and the transition rates calculated from it.

Table 2: Transition rates between foreclosure stages

The stages represented in the above transition matrix are limited by those that are tracked in the original data, which does not specify two special cases of foreclosures: short sales (when a lender agrees to let an owner sell a property for less than the amount owed on it) and deeds-in-lieu of foreclosure (when an owner voluntarily transfers title to the property to the lender prior to foreclosure). The first case reverts the property to stage 'C' (current on its loan) but may still impact proximate property values by lowering the neighborhood median value. The second case puts a property in the 'R' stage (REO, or real estate owned by lender) without passing through any intermediate stages of the foreclosure process. Our model, however, does not account for any intermediate stage effects, and only considers the starting and ending stages over the number of periods evaluated. Thus, for example, a property observed to be in REO in periods 1 and *t* is considered equivalent in terms of its impact on proximate property values regardless of whether it stayed in REO over the *t*-periods or reverted to current and then reentered foreclosure over this time frame.

The last set of data collected for the application of the PVI model, expected percent of proximate property value lost given foreclosure stage and distance, was adapted from the findings of Harding et al (2009). Their analysis estimated the percent discount on the resale price of a non-distressed property that is located in one of four distance ranges from a single foreclosure in one of 13 foreclosure stages. We used these parameters to derive linear functions of discount factors applicable to proximate properties at distances given in 50-foot increments from a foreclosure known to be in one of the five stages identified in the transition matrix above. As shown in Figure 3, these functions exhibited a steep negative relationship between discount factors and distance from a foreclosed property,[2] with the former tailing off considerably at distances greater than 500 feet.



Note: See Appendix B for details of this parameter conversion.

Figure 3: Proximate Property Value Discounts by Stage and Distance

Finally, to complete the calculations we assigned values to t = number of periods over which to estimate proximate property value impacts, and I = market interest rate from which to determine the present value of those losses. Following the methodology of the transition rates calculated with the Boston Fed data, we assumed each period to be one month long. The average time for loans in this database to go through the foreclosure process from initial foreclosure petition to auction[3] (when the property becomes REO) was just over seven months; for our base case calculations, therefore, we assumed a period of eight months over which the effects of foreclosures on proximate property values are assessed. To assign an appropriate interest rate to

[2] We believe that instances in our estimated curves that show increases in discount factors at farther distances are idiosyncratic to the data and do not represent real trends.

[3] Since all candidate properties considered in this analysis are already in the petition or REO stage, we set aside for the moment the average number of months that loans spend in the delinquency and default stages of the foreclosure process.

lost value calculations over this time frame, we referred to Boardman et al.'s (2010) analysis of optimal social discount rates for public investments; given the short time frame and lack of private investment crowd-out likely from CDC interventions, we thus chose an annual rate of 3.5% applied over each of our eight month-long periods.

Computational Results

With these parameters calculated, we applied the estimated discount factors to the assessed values of all properties proximate (within 500 feet) to each candidate foreclosure, given the foreclosure status of the candidate and the distance between each candidate and proximate property. The result was a list of total expected proximate property value losses associated with each acquisition candidate, which was ranked to identify those foreclosed properties that pose the greatest threat to neighborhood property values absent a CDC intervention. Appendix C shows the expected proximate property value losses for each of the 35 candidate properties identified by our community partner, which are also represented in Figure 4.

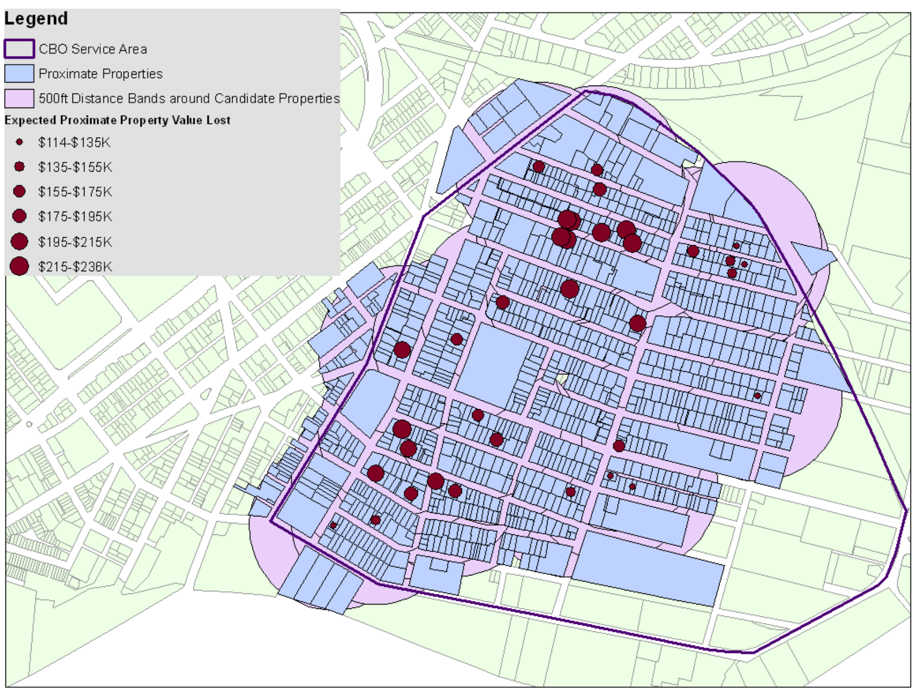


Figure 4: Map of Expected Proximate Property Value Impacts

The expected lost proximate property values associated with our set of candidate foreclosures ranged from $114,879 to $235,834, with a mean value of $181,421 and a median of $190,812.

Of the 35 candidate properties, three are single-family homes, which had a lower mean lost value estimate relative to larger properties: $150,808 versus $186,146 for the 12 two-family and $183,178 for the 20 three-family properties. This may reflect lower property density in areas around single-family homes. Properties already in the REO stage of the foreclosure process also had a higher average proximate property value impact, given the higher discount factors associated with this stage, and the high probability that a property in REO will stay in that stage over subsequent periods, owning to the long duration of this stage relative to others. Properties in REO at the time of analysis had an average impact of $194,099 in lost value to proximate properties, versus $173,787 for properties awaiting foreclosure auction and $180,707 for properties with only a foreclosure petition filed (See Tables 3 and 4).

Minimum	$114,879
Maximum	$235,834
Mean	$181,421
25th Percentile	$148,682
Median	$190,812
75th Percentile	$214,420

Table 3: Summary Statistics on Proximate Property Value Impacts

Distributions	Frequency	Average Proximate Property Value Impacts
By Property Type		
1-Fam	3	$150,808
2-Fam	12	$186,146
3-Fam	20	$183,178
By Foreclosure Status		
Petition	21	$180,707
Auction	8	$173,787
REO	6	$194,099

Table 4: Proximate Property Value Impacts by Property Type and Foreclosure Status

Sensitivity Tests

To test the sensitivity of these results to the baseline conditions chosen for the analysis, we re-evaluated the PVI model on the 35 candidate properties using alternative structural parameters. For example, changing the time frame from eight to four periods into the future (holding the interest rate at 3.5%) increased the expected lost value impact associated with each acquisition candidate by an average of 12.6%, reflecting the declining significance of foreclosures over time and the lower probabilities of a candidate property staying in a non-current foreclosure stage over the longer term. The rankings of candidate properties also changed slightly under the shorter timeframe, with then-REO properties increasing in rank relative to candidate properties in earlier stages of the foreclosure process, though the highest rated property in terms of expected lost value remained the same under both scenarios. Similarly, increasing the number of periods to 12 (holding the interest rate at 3.5%) reduced the expected lost value impacts relative to the baseline[4] by an average of 6.4%, with all REO properties declining in the rankings relative to non-REO properties.

Reducing the prevailing interest rate from 3.5% to 2.0% (holding the number of periods to eight) had the same directional effect as decreasing the number of periods, with lost value estimates increasing by 1.0% for all candidate properties. Increasing the interest rate to 5.0% likewise reduced expected lost value impacts by 1.0%. Since these changes were identical across all candidate properties, increasing the interest rate had no effect on the relative ranking of acquisition candidates.

Additional tests were conducted to evaluate any sensitivities in the model to the values in the transition matrix used in the analysis by comparing Chelsea with other markets in Massachusetts that are viewed as generally weaker (e.g. fewer sales out of early foreclosure stages, more time spent in REO) and stronger (e.g. more sales out of early foreclosure stages, less time spent in REO). To initially identify such markets, we used external rankings of all zip codes in the state according to their foreclosure risk, as calculated by the Local Initiatives Support Corporation (LISC)[5] in the first quarter of 2010. The transition matrices associated with these markets, however, were not as expected; instead of reflecting transition rates that were either higher or lower than Chelsea's rates, both matrices had rates that indicated fewer loans staying in the

[4] The reduction in impacts assessed over longer time frames may suggest that CDCs can wait out the negative effects from foreclosures rather than intervening to maintain neighborhood stability, since all foreclosed properties will eventually revert to current. This logic, however, ignores any potential long-term consequences for neighborhood quality due to foreclosures that are not captured in the short-term losses to proximate property values. Such long-term effects include changes in resident socio-economic characteristics, reduced private and public investment in the neighborhood, and a deepened association with crime and blight (Kingsley, 2009; Li & Morrow-Jones, 2010). This model also does not consider how declines in proximate property values increase the risk that these properties might also fall into foreclosure and have their own proximate property value impacts.

[5] State-specific and metro-specific rankings of zip codes by quarter for the country are available at http://www.foreclosure-response.org/maps_and_data/lisc_data.html.

'Current' stage across periods, but also fewer staying in the 'REO' stage of the foreclosure process; see Appendix D for more detail on these transition matrices and explanations for these findings. When these two matrices were applied to the PVI model, however, the total proximate property value impacts associated with the 35 candidate properties did change as expected, i.e. expected total PVI declined for all properties under both scenarios relative to Chelsea transition rates. The so-called 'stronger' markets did have a larger reducing effect on average PVI, which declined by 4.2% to $173,704, versus a 1.4% decline to $178,737 for 'weaker' markets.

The following two graphical representations of these sensitivities show how the PVI model responded to changes in its baseline parameters. The first is a Tornado diagram, which is often used to demonstrate the magnitudes of different parameter changes when a number of alternative specifications are modeled. Figure 5 presents the Tornado diagram for changes in the PVI model from different periods, interest rates, and our evaluation of market strength, and shows how these changes alter the computational results of the model. This diagram, however, does not consider the relative scale effects (e.g. proportionality) or directionality of parameter changes.

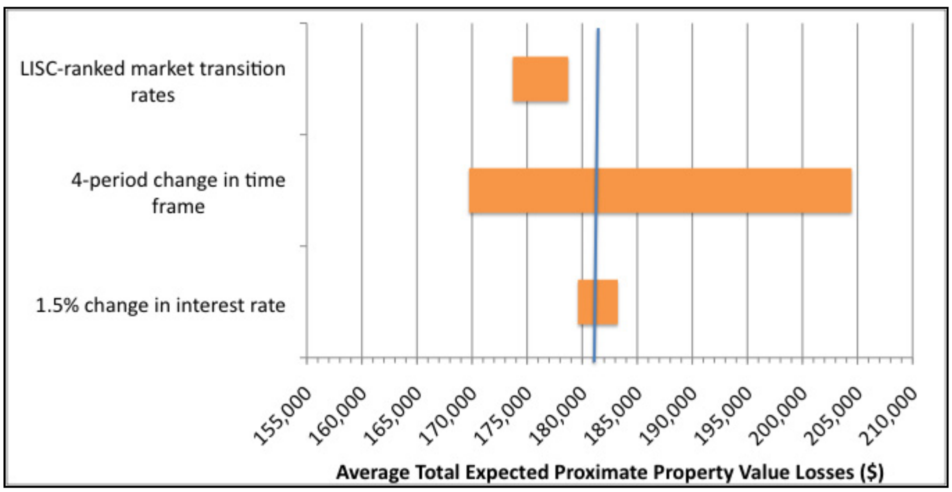


Figure 5: Magnitude of Impacts on PVI of Changes in Model Parameters

Another option to compare model sensitivities is with spider plots, which do include magnitude, directionality, and relative scale effects in a graphical representation of parameter changes. The downside of spider plots is that such changes are expressed in terms of percent deviations from a baseline value; parameters that do not correspond to discrete numerical representations, such as the transition matrices representing different market conditions, are thus difficult to display. The

PVI model sensitivity tests of interest rate and time period, however, are demonstrated in a spider plot in Figure 6.

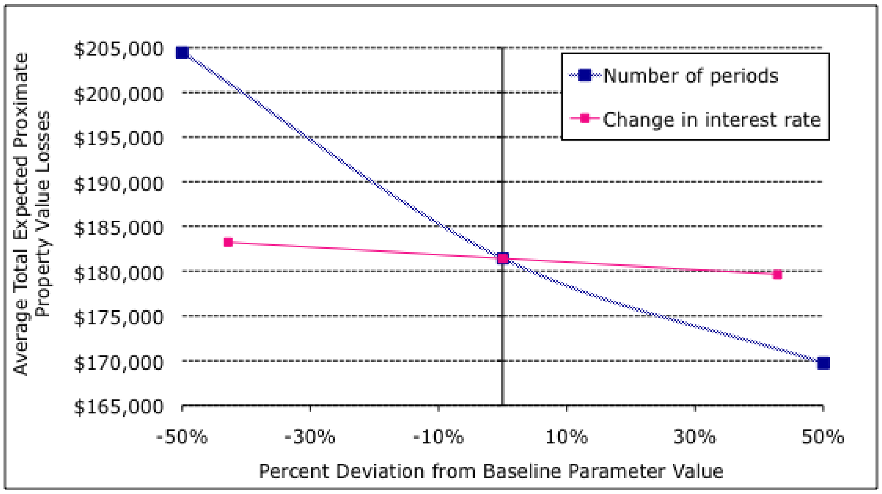


Figure 6: Scale and Directionality of Impacts on PVI of Changes in Model Parameters

7. Analysis and Implications

For the 35 candidate foreclosed properties evaluated in this analysis, the average proximate PVI was $181,421, and ranged from $114,879 to $235,834, with some sensitivity to changes in assumptions/parameters. Of these candidate properties (as identified in October 2009), our partner CBO eventually purchased three of them, which were ranked 4th, 6th, and 32nd in terms of expected proximate PVI in our model. Based on the estimates in our model, therefore, a total of $580,000 in proximate property value losses was potentially averted through these purchases. Had the CBO purchased the top three properties by expected proximate PVI, however, the total averted lost proximate property value would have been $705,500.

The estimates of the expected proximate property value losses calculated with the PVI model provide a reasonable measure of the potential social impacts associated with a set of foreclosed properties, absent the acquisition of any foreclosed properties by a CBO. This information can assist CBOs considering acquisitions of such properties to improve neighborhood stabilization in the face of widespread foreclosures. In particular, the PVI model provides insight on both the probabilities of future outcomes for current candidate properties, and on the efficient allocation of limited resources to achieve mission objectives. In the case of our partner CBO, the 35 foreclosed properties considered in October 2009 have a wide range of estimated proximate property value impacts, with a handful of these properties ranking, according to this metric, as primary candidates for acquisition.

It is important to stress that these estimates are one tool available to CBOs engaged in foreclosure acquisitions for neighborhood stabilization, and are intended to supplement the considerable level of local knowledge and market expertise that many such organizations already possess. Property value impacts are also only one type of criterion that CBOs may use in evaluating candidate properties; other considerations suggested by practitioners include the total acquisition and expected redevelopment costs associated with a given property, the probability of successful acquisition and redevelopment of a property to community standards given budget constraints, the strategic value associated with certain property locations and types, and the implications for community equity from choosing among alternative acquisition opportunities. A complete evaluation of candidate foreclosed properties thus requires further models to address these additional criteria, some of which are in development concurrent to the PVI model described in this paper.

The PVI model also has implications for policy development at the local and national level. The Neighborhood Stabilization Program (NSP), for example, is a federal program that provided nearly $7 billion to states, municipalities, and some CBOs directly to address the foreclosure crisis through acquisitions and other foreclosure mitigation activities. Information such as that produced with the PVI model could be used to improve the allocation of those funds towards communities and properties estimated to have the greatest potential negative impact on the surrounding neighborhood. Likewise, state and local initiatives to facilitate foreclosure acquisitions by CBOs, such as the CHAPA First Look program in Massachusetts, can use the PVI model to help CBOs better assess their options and target their neighborhood stabilization efforts.

From a research perspective, the PVI model represents a novel application of cost-benefit analyses to a prospective decision problem. It is the first such application to use a Markov chain to model transitions across foreclosure states to impute property value impacts. It is also the first known use of decision models intended to assist community-based organizations responding to the foreclosure crisis.

8. Model Validity and Limitations

The PVI model, for all its potential benefits to CBOs and policymakers, does have some limitations that should be acknowledged. These limitations reflect both the assumptions used in the development of the model and the data used to operationalize the model for our case study of candidate foreclosed properties in Chelsea, MA. It may be possible with further research and data collection to address these limitations directly, but for now we simply note the most relevant among them and their possible impacts on model validity.

Non-linearities in aggregate impacts

As mentioned in section 3 above, we assume in the PVI model that the total proximate property value impact associated with a foreclosure is the sum of its impacts on each individual proximate property (see also Equation 6), and that all candidate foreclosed properties considered for acquisition by a CDC are in one neighborhood with consistent residential density and market characteristics. It is worth considering, however, how sensitive the PVI model is to these assumptions and how our output might differ if they were relaxed. If, for example, second order effects from the impact of a single foreclosure on proximate properties were allowed (separate from any captured in the discount factors already applied in the model), the additivity of proximate property value impacts could vary with the strength of the real estate market. One option for making such an adjustment is to raise the summed effects across proximate properties to a power less than one in strong markets (i.e. reducing the total impact calculated) and greater than one in weaker markets (i.e. increasing the total impact calculated). Additional research that explicitly models such market differences would produce more reliable and practical results for CBOs operating in different markets, and could also suggest policy changes to address these different outcomes in communities across the country.

Long-term analysis

The PVI model considers a relatively short time frame for analysis of potential foreclosure impacts on proximate property values, in part to limit any influence from longer-term market changes that may impact foreclosure outcomes on neighborhood conditions. A simplified and more generalized approach to the lost value calculation, however, may involve the proportion of time π_i, as calculated in Equation 2 above, that a property is in state i. Using an appropriate time-based lost value function for each distance category and the values of π_i, such an analysis could calculate the expected value loss due to each property over a longer time horizon than with the current PVI model. Multiplying these values by the number of properties in that distance category, would obtain a specific value for each property representing the expected value loss due to foreclosure related factors. Note that this is a steady-state based analysis, and the results will be sensitive to the transition probabilities in the model; in general, the expected loss will be higher in dense neighborhoods. However, such analysis will be invalid if the time-homogeneity assumption is relaxed, which indeed should be the case in long term planning. Hence, this alternative model can only be used for general guidance and possible verification purposes. Moreover it requires neighborhood-specific analysis and an accurate estimation of transition probabilities not currently permissible with available data.

Non-stationary Markov chains

The PVI model assumes that the transition rates for foreclosure stages are time-invariant and not sensitive to market conditions or policy changes that may impact the duration or probability of distressed properties moving through specific foreclosure states. This assumption, while necessary for modeling purposes, is not necessarily realistic; indeed, at the end of the period from which the loans in the transition matrix were evaluated, the Commonwealth changed its law with respect to the length of time that lenders are required to give property owners to resolve or restructure their delinquent loan after a foreclosure filing, increasing it from 90 to 150 days. Such a change is certain to impact the rate at which loans move through the foreclosure process and the share that progress to the REO stage versus reverting to current following a payoff or loan modification. Relaxing the stationary Markov chain assumption is thus one option for future research, and in particular any examination of how policy changes, such as the one in Massachusetts at the end of 2010, impact foreclosure outcomes for communities.

Representativeness of data sources

Another concern about the PVI model, which was raised by our community partner during the early stages of model development, is that the discount factors used in this analysis are drawn from a national sample of non-distressed properties proximate to known foreclosures, and may not represent actual foreclosure impacts on proximate property values in a specific market. Indeed, such impacts are quite likely to vary by market and neighborhood conditions, with stronger markets experiencing somewhat less impact to neighborhood property values from a proximate foreclosure, and vice versa for weaker markets (see, e.g. Mallach, 2008). As such, these results are not intended to be estimates of the actual property value impacts associated with individual foreclosures; more important than the absolute quantities associated with candidate properties is the variation over space represented by these stylized estimates, which should be interpreted as a *relative* measure of impacts across a set of candidate foreclosed properties being considered for acquisition by a CBO.

Sensitivity to transition rates

As the sensitivity tests in section 6 above demonstrate, the PVI model results are sensitive to the selection of the foreclosure transition rate matrix used in the estimation. Since the matrix used in our baseline estimate reflects observed transition rates among properties in Chelsea only, its use is appropriate to our case study; however, caution should be used in interpreting or extrapolating these results to other locations, particularly those with different housing stocks, densities, assessed values, and market conditions relative to Chelsea, at least until additional analysis on transition rates and candidate properties can be conducted on other markets.

Impacts of multiple foreclosures

The PVI model is concerned with the impacts of a single foreclosure, but does not consider how such impacts might be influenced by the presence of multiple foreclosures within a neighborhood, though this has been the subject of prior research on foreclosure effects. Harding et al (2009), for example, explicitly modeled for this effect in their analysis, finding that over a small number of proximate foreclosures (up to 10 within 2000 feet of the observed non-distressed property) property value impacts increase in a roughly linear fashion. Over a larger number of foreclosures, however, this assumption is unlikely to hold, since a property that is surrounded by a high concentration of foreclosed properties could in theory lose all its value, which is implausible. Market strength may also cause variations in the effect of multiple foreclosures (Lin et al, 2009), as could the clustering of multiple foreclosures within a small area (Schuetz et al, 2008).

Wider range of social impacts

Finally, the PVI model uses the assessed value of properties proximate to a foreclosure as a proxy for a set of unobserved social impacts assumed to be capitalized in those values. Little research has been done, however, to confirm exactly which effects are so captured and which are not. Such research is generally outside the scope of traditional decision science practice, but could benefit future work on decisions models for foreclosure acquisition activities by CBOs.

Limitations such as these can call into question the validity of a model that seeks to replicate a real-world phenomenon, particularly one that is difficult to directly observe and quantify. We can, however, retain some internal validity by confirming the appropriate use and application of the assumptions and conceptual framework used in the PVI model. The Markov chain is used consistent with its purpose as described by Ross (2009) to assess probabilities of uncertain future outcomes conditional on the current state of a stochastic process. The PVI model itself estimates the potential social impacts associated with a foreclosure, following the framework described by Boardman et al (2010) to calculate the present value of such effects at some point in the future. This approach is common in sophisticated models of real-world phenomena to compute the social costs and benefits appropriate for policy analysis. Thus while the use of these concepts to possible acquisition candidates considered by a CBO for neighborhood stabilization in this paper is novel to the OR field, their application is consistent with established theoretical and practitioner conventions in decision science.

In addition to internal validity, the PVI model seeks to achieve external validity with respect to the consistency of the computational results with the true social impacts associated with a foreclosure. However, given the exploratory nature of the PVI model, complete validation of results is not possible. Indeed, the only other analysis we are aware of that sought to model the effects of individual foreclosures on proximate property values is the national estimation calculated by the Center for Responsible Lending (2009); any attempt to compare our local estimates with these results would be irresponsible and unproductive. We can, however, increase our external validity by using, whenever possible, data from practitioners and researchers in the housing field on real-world foreclosure processes and outcomes, including transition rates on loans in Chelsea as computed by the Federal Reserve Bank of Boston, findings by Harding et al (2009) on the discount factors applicable to the value of properties proximate to a foreclosure, and a set of actual candidate foreclosed properties considered by our community partner CBO as of October 2009. We further assess external validity by testing the effect of changes in key model parameters, such as the interest rate, number of periods, and market strength as represented by transition probabilities; to the extent our results appear to be robust to such changes, we can be reasonably assured of the PVI model's external validity.

9. Conclusion and Next Steps

The model developed in this paper represents the first known attempt to apply a Markov chain to the analysis of foreclosure stages for possible acquisition opportunities, and the first use of decision models for the purpose of assisting a CBO with their foreclosure acquisition activity. The estimated impacts provide a baseline measure of the expected aggregate impacts on proximate properties from a single foreclosure, and a sense of the relative scale of such impacts across potential acquisition properties, which are a proxy for a range of social impacts associated with foreclosures. Given the limitation that national data used in this model do not reflect local trends, our results seem plausible and consistent with intuition.

Our results not only have the potential to increase the efficiency and outcomes for CBOs engaged in foreclosure acquisitions for neighborhood stabilization, but to also influence policies that fund and assist such CBOs in their missions. For example, if CBOs believe that PVI is an important criterion for acquisition decisions, and if CBOs were to choose properties that are not at the top of a rank-ordered list of PVIs, then they may wish to ensure that estimated impacts on other dimensions compensate for lower estimated PVIs.

We hope this research will lead to additional applications of decision models to foreclosure acquisition decisions, as well as reconsideration of some of the PVI model's assumptions discussed in this paper. In particular, we would like to see more research that addresses some concerns raised by practitioners with respect to the current PVI model and its applicability to local market analyses. The PVI model would also benefit from additional study of the social impacts of foreclosures, especially those that can be isolated and quantified for use in decision models. Some applications of the PVI model include decision models that assess the strategic nature of different investment alternatives over time and across a large and heterogeneous study area, models that help manage a portfolio of acquired units over time by a CBO operating in a small area, and models that develop different strategies for bidding on properties in a small area. Each of these decision models assumes the existence of and relies on some measure of the social value and impact of foreclosed properties. The PVI model, while providing only one crude approximation of such a measure, is thus vital to the future development of decision models for CBO foreclosure efforts.

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For additional information on this and other work regarding foreclosure acquisitions decisions by CBOs, please visit http://umb.libguides.com/foreclosed_housing.

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APPENDIX A: Estimation of Transition Rates among Foreclosure Stages for Markov Chain

The estimated transition rates for loans across different stages of the foreclosure process used in the Markov chain of foreclosure stage probabilities was derived from data analyzed by researchers at the Federal Reserve Bank of Boston, using information on all first-lien loans active in 2010 in Massachusetts collected from The Warren Group and Lender Processing Services (LPS). This data was used to track loans monthly across nine different stages of the foreclosure process:

- C=Current (not delinquent or in foreclosure)
- 3=30 days delinquent
- 6=60 days delinquent
- 9=90 days delinquent
- F=In foreclosure (petition filed, pre-auction)
- R=Post-auction, generally REO, but can also reflect properties sold at auction to a third-party and "held" by the lender before they are officially sold to the third-party buyer
- 0=Paid off (no longer an active loan)
- L=Involuntary liquidation (sale of property by lender, with no linked information on any subsequent loans taken out on the property)
- T=Transferred to a different servicer (no longer tracked)

The first six stages above are transitional stages of the foreclosure process, from which loans could enter or exit in a given month. The last three stages, however, are terminal stages in the data; loans entering these stages are no longer tracked through subsequent transitions in the foreclosure process.

Analysis of all active loans in Chelsea in 2010 yielded the following counts of loans transitioning into each of these states in each month:

	Status in t+1									
Status in t	**C**	**3**	**6**	**9**	**F**	**R**	**0**	**L**	**T**	**Total**
C	522	77	1	0	0	0	0	0	2	602
3	29	81	80	0	0	0	0	0	0	190
6	9	20	38	62	1	1	0	0	0	131
9	21	4	12	475	58	1	1	2	2	576
F	10	0	0	19	346	17	0	6	2	400
R	0	0	0	0	0	66	1	4	0	71
Total	591	182	131	556	405	85	2	12	6	1,970

For use in a Markov chain of conditional probabilities, some adjustments to this data were required:

1. Since our perspective is properties, any property that is not delinquent, in default, in foreclosure, or REO is viewed as 'current', regardless of whether this state was achieved by the borrower becoming current on his loan, by the borrower paying off his loan, by the borrower selling to a new buyer after a short sale, or by the lender in a post-REO sale. Thus, loans in stages C, 0, and L are functionally equivalent for our purposes, and were combined into our 'Current' stage.
2. Loans that were 30 or 60 days delinquent were combined and used as our 'Delinquent' stage, while loans 90 days delinquent were treated as 'Default'
3. The 6 loans that transitioned to another servicer (state "T") were subtracted from the analysis; as a terminal state, inclusion of loans in T would violate the irreducible condition needed for the Markov model.

Thus done, the counts of all 2010 Chelsea loan transitions through the five stages in the PVI model became:

	Status in *t*+1					
Status in *t*	**C**	**DQ**	**DF**	**F**	**R**	**Total**
C	522	78	0	0	0	600
DQ	33	74	537	59	2	705
DF	24	16	475	58	1	574
F	16	0	19	346	17	398
R	5	0	0	0	66	71
Total	605	313	556	405	85	1964

Expressed as row percentages:

	Status in *t*+1				
Status in *t*	**C**	**DQ**	**DF**	**F**	**R**
C	0.870	0.130	0.000	0.000	0.000
DQ	0.047	0.105	0.762	0.084	0.003
DF	0.042	0.028	0.828	0.101	0.002
F	0.040	0.000	0.048	0.869	0.043
R	0.070	0.000	0.000	0.000	0.930

It is worth noting that the periods used in this transition matrix and the PVI model itself are months, while the stages specified in the analysis of foreclosure discount factors by Harding et al (2009), which are used to develop the discount parameters in the PVI model, are quarters (3 months). There is also a time inconsistency with respect to the period of observation between the transition matrix data and Harding et al (2009); the latter uses observed sales of non-distressed properties proximate to a foreclosure (nationally) between 1989 and 2007, while the former is based on loan counts (in Chelsea, MA only) in 2010. The data on candidate properties in a particular neighborhood of Chelsea, MA to which the PVI model is applied, meanwhile, is based on foreclosure status as of October 2009. Unfortunately, due in part to the exploratory nature of this model, we are unable to use consistent data with respect to both time and location in the PVI model, and note this limitation of our model for academic purposes.

APPENDIX B: Calculation of Parameters for Discount Factors Applied to Proximate Property Values

To operationalize the PVI model, we based our calculations of the discount factors applicable to the values of properties proximate to a candidate foreclosure, i.e. $y_{ph}(i,d)$, on the proximity-based property value loss estimates given by Harding et al (2009). These value losses are the estimated percent discount on the resale price of a non-distressed single-family property associated with the presence of at least one nearby foreclosed unit, after accounting for other neighborhood and market characteristics that could also impact the resale price.[6] In Harding et al (2009), the discount rate is assumed and statistically shown to vary with the distance between the two properties (given in bands of 0-300 feet, 300-500 feet, 500-1000 feet, and 1000-2000 feet) and the stage of the foreclosure process of the distressed unit at the time of resale (measured in 3-month intervals over the year before and after the foreclosure filing and up to a year after a foreclosure auction or sale to the lender).

Estimated Proximate Property Value Discounts by Distance and Stage of Foreclosure

Stage	Ring 1 (0-300 ft)	Ring 2 (300-500 ft)	Ring 3 (500-1000 ft)	Ring 4 (1000-2000 ft)
F-12 to F-9	-0.15	-0.14	-0.10	-0.15
F-9 to F-6	-0.19	-0.19	0.00	0.00
F-6 to F-3	-0.43	-0.16	-0.20	-0.05
F-3 to F	-1.08	-0.17	-0.20	-0.05
F to F+3	-0.83	-0.15	-0.15	-0.05
F+3 to F+6	-0.96	-0.17	-0.15	-0.05
F+6 to F+9	-0.69	-0.52	-0.22	0.00
F+9 to F+12	-0.81	-0.31	-0.15	-0.05
S to S+3	-0.97	-0.81	-0.18	-0.05
S+3 to S+6	-0.97	-0.51	-0.20	0.00
S+6 to S+9	-0.83	-0.48	-0.15	0.00
S+9 to S+12	-1.05	-0.14	-0.10	0.00

Note: Stages are 3-month periods before (-) and after (+) the foreclosure filing (F) and the REO sale (S). The discount impacts for Rings 3 and 4 are estimated from a graphical representation. Source: Harding et al. (2009).

[6] Harding et al (2009) do not have data on property-level characteristics that might influence the resale price, such as renovations or new amenities added by prior owners. To adjust for this, they removed from the analysis all resales with more than 8% average quarterly price appreciation, or more than 10% average quarterly price appreciation for resales within two years.

For the PVI model, we adapted these discount rates into piecewise linear functions[7] of the distance between candidate and proximate properties (*d*). Using visual and numerical data included in Harding et al (2009), we calculated slopes and intercepts for each segment of the function between the midpoints of the four rings. A few notes on this process are worth mentioning here:

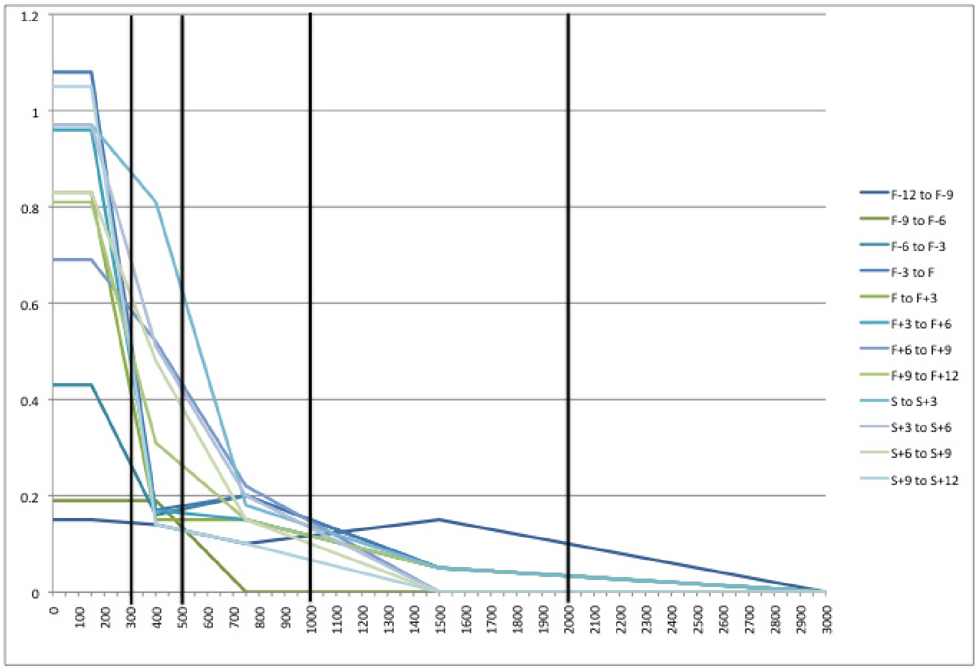
- For curve fitting purposes, we assumed that the value loss for properties that are between 0-150 ft (midpoint of ring 1) is equal to that given for ring 1. Similarly, the losses at midpoints of other rings (400 ft, 750 ft, 1500 ft) are defined as being equal to the given values for that ring. A value loss rate of 0 is assumed for distances greater than or equal to 3000 ft.
- For some foreclosure stages, the data does not follow a non-increasing (in absolute terms) trend. Such data points were treated as anomalies, and either ignored or replaced with an estimate for that distance range.
- Based on some experimental regression analysis, it can be concluded that for most stages the data does not suggest a good linear or quadratic fit. This is somewhat expected given that we have only four data points. Hence, any linear/non-linear functions that we fit to this data are likely not going to be accurate in representing the proximity-based impacts.
- As it is mostly the case in the absence of data or any clear trends, it would be most appropriate to use piecewise linear functions to represent the relationship between distance and value loss in our model. Given that we only need this information for numerical calculation purposes, i.e. not for numerical optimization, such piecewise linear representations will not be of concern computationally.

[7] While a smooth, non-linear function of discount rates with respect to distance from a foreclosed property are likely more realistic, we are limited in our analysis by the distance rings used in the source data. With only four such data points, therefore, we estimate these piecewise linear functions as an approximation of the assumed reality of this relationship.

The parameters thus derived were:

		Segment 1 150-400 ft	Segment 2 400-750 ft	Segment 3 750-1500 ft	Segment 4 1500-3000 ft
F-12 to F-9	Slope	-0.00004	-0.00011	0.00007	-0.00010
	Intercept	0.15600	0.18571	0.05000	0.30000
F-9 to F-6	Slope	0.00000	-0.00054	0.00000	0.00000
	Intercept	0.19000	0.40714	0.00000	0.00000
F-6 to F-3	Slope	-0.00108	0.00011	-0.00020	-0.00003
	Intercept	0.59200	0.11429	0.35000	0.10000
F-3 to F	Slope	-0.00364	0.00009	-0.00020	-0.00003
	Intercept	1.62600	0.13571	0.35000	0.10000
F to F+3	Slope	-0.00272	0.00000	-0.00013	-0.00003
	Intercept	1.23800	0.15000	0.25000	0.10000
F+3 to F+6	Slope	-0.00316	-0.00006	-0.00013	-0.00003
	Intercept	1.43400	0.19286	0.25000	0.10000
F+6 to F+9	Slope	-0.00068	-0.00086	-0.00029	0.00000
	Intercept	0.79200	0.86286	0.44000	0.00000
F+9 to F+12	Slope	-0.00200	-0.00046	-0.00013	-0.00003
	Intercept	1.11000	0.49286	0.25000	0.10000
S to S+3	Slope	-0.00064	-0.00180	-0.00017	-0.00003
	Intercept	1.06600	1.53000	0.31000	0.10000
S+3 to S+6	Slope	-0.00184	-0.00089	-0.00027	0.00000
	Intercept	1.24600	0.86429	0.40000	0.00000
S+6 to S+9	Slope	-0.00140	-0.00094	-0.00020	0.00000
	Intercept	1.04000	0.85714	0.30000	0.00000
S+9 to S+12	Slope	-0.00364	-0.00011	-0.00013	0.00000
	Intercept	1.59600	0.18571	0.20000	0.00000

Graphically:



The next step in the adaptation process was to convert the twelve foreclosure stages used by Harding et al (2009) into the five stages specified in the PVI model's transition matrix, as shown:

Harding et al (2009)	PVI model
F-12 to F-9 F-9 to F-6	Delinquency (DQ)
F-6 to F-3 F-3 to F	Default (DF)
F to F+3 F+3 to F+6 F+6 to F+9 F+9 to F+12 (or until S)	Foreclosure (FC)
S to S+3 S+3 to S+6 S+6 to S+9 S+9 to S+12 (or until sale to new owner)	REO

We assume that properties in the C (current) stage of our model do not have any lost value impacts on proximate properties, and thus do not correspond with any of the time periods in the Harding et al (2009) analysis. The result is five piecewise linear functions of the expected discount on proximate property values from a single distressed property, given the stage of the foreclosure process that property is in and its distance to any given proximate property.

APPENDIX C: PVI Model Results on Chelsea Candidate Foreclosed Properties

Candidate properties	Property type	Foreclosure stage as of October 2009	Number of proximate properties	Aggregate proximate property value	Average proximate property value	Number of proximate properties also in foreclosure	Total expected proximate property value lost (baseline)
15 S St	3-Fam	Petition	115	$36,817,900	$320,156	3	$114,879
20 U St	3-Fam	Petition	144	$40,994,400	$284,683	5	$150,381
78 E St	3-Fam	Petition	184	$55,508,200	$301,675	7	$191,921
99 V St	3-Fam	Petition	141	$41,053,800	$291,162	3	$139,421
139 O Av	2-Fam	Petition	188	$55,635,000	$295,931	7	$190,812
130 V St	3-Fam	Auction	105	$39,391,900	$375,161	3	$120,893
129 O Av	3-Fam	Auction	191	$57,833,700	$302,794	8	$200,396
71 H St	2-Fam	Petition	126	$37,576,800	$298,229	3	$127,563
60 E St	2-Fam	Petition	167	$58,001,500	$347,314	7	$197,472
110 O Av	3-Fam	Petition	173	$63,607,000	$367,671	7	$208,469
81 H St	3-Fam	Petition	149	$48,515,100	$325,605	3	$159,831
56 V St	2-Fam	Petition	174	$55,537,700	$319,182	3	$186,697
7 V St	2-Fam	REO	161	$62,297,900	$386,943	7	$225,967
67 C Av	2-Fam	Petition	157	$50,846,400	$323,862	6	$167,896
192 T Av	1-Fam	Petition	106	$36,734,600	$346,553	0	$134,106
120 S St	3-Fam	Petition	128	$63,699,600	$497,653	2	$200,346
120 W St	2-Fam	Petition	137	$53,123,600	$387,764	3	$170,280
140 H St	2-Fam	REO	160	$60,399,400	$377,496	2	$210,130
7 T St	1-Fam	REO	136	$50,785,700	$373,424	2	$191,766
81 B St	2-Fam	Petition	180	$67,019,700	$372,332	9	$218,710
134 G St	3-Fam	Petition	122	$39,773,300	$326,011	4	$146,983
139 M St	3-Fam	Auction	110	$34,439,600	$313,087	4	$125,604
131 M St	2-Fam	Auction	115	$37,011,500	$321,839	4	$137,169
115 M St	3-Fam	Auction	132	$47,341,100	$358,645	6	$161,845
148 M St	1-Fam	REO	104	$32,608,600	$313,544	4	$126,554
88 G St	3-Fam	Petition	167	$61,009,100	$365,324	11	$220,760
61 G St	3-Fam	Petition	193	$69,397,600	$359,573	10	$227,447
57 G St	2-Fam	Petition	190	$69,927,200	$368,038	10	$226,346
74 G St	3-Fam	Auction	175	$66,839,200	$381,938	9	$234,672
75 M St	3-Fam	REO	163	$60,535,200	$371,382	10	$235,834
62 G St	3-Fam	Auction	181	$69,447,400	$383,687	10	$235,007
60 G St	3-Fam	Petition	182	$63,807,800	$350,592	10	$222,077
57 L St	3-Fam	Petition	155	$55,297,100	$356,755	9	$192,452
52 L St	3-Fam	REO	132	$46,011,900	$348,575	9	$174,347
17 L St	2-Fam	Auction	114	$51,176,400	$448,916	6	$174,711

Note: Street names are coded with single letters to anonymize actual addresses evaluated.

APPENDIX D: Sensitivity Tests on Market Conditions

To test the sensitivity of applying the PVI model to a particular market, we selected a set of both 'weaker' and 'stronger' markets relative to Chelsea from which to calculate transition rates and effects on PVI results. This selection was made using data from the Local Initiatives Support Corporation (LISC) on the relative rankings of all zip codes in Massachusetts according to their foreclosure risk scores as of the first quarter of 2010. These scores are calculated by LISC each quarter as a service to grantees of Neighborhood Stabilization Program (NSP) funds to help identify areas within a state that have the greatest need for foreclosure interventions. Four components go into assessing the score for each zip code: the share of mortgages in foreclosure, the share of mortgages that are 30+ days delinquent (as an indicator of future foreclosures), the share of mortgages that are subprime, and the share of occupied units that are vacant. Additional information on the data and methodology for these scores can be found at http://www.housingpolicy.org/assets/foreclosure-response/zipmethodology.pdf.

There are 480 zip codes in the LISC data for Massachusetts; when ranked by their foreclosure risk scores in Q1 2010 from highest risk to lowest risk, the 02150 zip code that comprises all of Chelsea ranks 39th, or in the top 10% of all zip codes in the state for foreclosure risks. Taking a subset of these zip codes for which Chelsea has the median foreclosure risk score (i.e. the worst 78 zip codes), we divided this group into quartiles and designated the top quartile (i.e. the worst 19 zip codes) as a set of 'weaker' markets and the bottom quartile (i.e. the 60th-78th worst zip codes) as a set of 'stronger' markets, relative to Chelsea. These zip codes were:

Weaker Markets		Stronger Markets	
Zip Code	**Place Name**	**Zip Code**	**Place Name**
01109	Springfield	02719	Fairhaven
02301	Brockton	01826	Dracut
02302	Brockton	01852	Lowell
01104	Springfield	01904	Lynn
01108	Springfield	01757	Milford
02124	Boston	02346	Middleboro
01841	Lawrence	02072	Stoughton
02740	New Bedford	02128	Boston
01420	Fitchburg	02744	New Bedford
01902	Lynn	01570	Webster
02780	Taunton	01970	Salem
02151	Revere	01129	Springfield
02368	Randolph	01069	Palmer
02360	Plymouth	01906	Saugus
01201	Pittsfield	01602	Worcester
02126	Mattapan	02601	Hyannis
02121	Boston	02760	North Attleboro
01119	Springfield	01832	Haverhill
02136	Hyde Park	02571	Wareham

Using aggregated loan transition data from the Federal Reserve Bank of Boston from all loans that were active in 2010 in the zip codes in each of these two sets, we calculated the following two transition rate matrices:

'Weaker' markets

	Status in *t*+1				
Status in *t*	**C**	**DQ**	**DF**	**F**	**R**
C	0.845	0.153	0.001	0.000	0.000
DQ	0.133	0.717	0.147	0.004	0.000
DF	0.050	0.031	0.851	0.066	0.002
F	0.027	0.003	0.056	0.873	0.041
R	0.068	0.000	0.003	0.009	0.920

‘Stronger’ markets

	Status in *t*+1				
Status in *t*	**C**	**DQ**	**DF**	**F**	**R**
C	0.834	0.165	0.001	0.000	0.000
DQ	0.133	0.713	0.148	0.006	0.000
DF	0.054	0.031	0.845	0.069	0.001
F	0.029	0.002	0.055	0.878	0.037
R	0.079	0.000	0.002	0.009	0.910

The differences between these matrices and the transition rate matrix for Chelsea (see Appendix A) are for the most part minor, with a few exceptions. Both the weaker and stronger markets' matrices report much higher shares of delinquent loans staying delinquent in the following month (71.7% and 71.3% in weaker and stronger markets, respectively, versus 10.5% in Chelsea) and lower shares transitioning to default (14.7% and 14.8%, versus 76.2% in Chelsea). The above matrices also report lower shares of loans staying current from one month to the next (84.5% and 83.4%, versus 87% in Chelsea), but also lower shares of REO loans staying in REO (92% and 91%, versus 93% in Chelsea). These are not what we expected to find; we expected that only weaker markets would have lower shares of loans staying current (i.e. more loans in some stage of foreclosures) and higher shares of loans staying in REO, with the opposite occurring in stronger markets.

There are a few possible explanations for these discrepancies. First, the selections of ‘weaker’ and ‘stronger’ markets relative to Chelsea were both comprised of zip codes that rank in the top sixth for foreclosure risks across Massachusetts – in other words, they are all weak markets relative to the rest of the state. Variation among them in foreclosure problems and market conditions may thus not be that great. Second, we selected these markets based on a different conception of what constitutes a ‘weak’ versus a ‘strong’ market than our own view, which considers the speed with which properties flow through and out of the foreclosure process. The LISC scores, on the other hand, are based on static rates of foreclosures, delinquencies, vacancies, and sub-prime loans – the latter two conditions being irrelevant to our idea of market condition vis-à-vis foreclosure impacts on proximate property values. Finally, since the foreclosure risk conditions in a zip code can change over time, rankings of zip codes on such a metric in the first quarter may not be representative of how that market faired for the entire year over which the loan transition data was collected. While this was observed some of the ‘stronger’ markets (7 of 19 moved out of the set in subsequent quarters), only one of the ‘weaker’ market zip codes improved out of its set over the year (from 19^{th} in the first three quarters of 2010 to 22^{nd} in the fourth quarter).

Though the transition matrices calculated for ‘weaker’ and ‘stronger’ markets were not as expected, their application to the PVI model did perform as intended. Given that both matrices showed slightly better rates of transition out of REO, both resulted in slightly lower average proximate PVI – 1.4% lower among ‘weaker’ markets and 4.2% lower among ‘stronger’ markets, relative to the baseline average PVI calculated with Chelsea transition rates.