MEASURING THE IMPACTS OF COMMUNITY DEVELOPMENT INITIATIVES

A New Application of the Adjusted Interrupted Time-Series Method

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The authors contribute to the development of empirical methods for measuring the impacts of place-based local development strategies by introducing the adjusted interrupted time-series (AITS) approach. It estimates a more precise counterfactual scenario, thus offering a stronger basis for drawing causal inferences about impacts. The authors applied the AITS approach to three community development initiatives using single-family home prices as the outcome indicator and found that it could measure impacts on both the base level of prices and the rate of price appreciation. The authors also found a situation in which the method appears unreliable, however. The AITS approach benefits from more recurrent data on outcomes during the pre- and post-intervention periods, with an intertemporal pattern that avoids great volatility. The AITS approach to measuring effects of community development initiatives holds strong promise, with caveats.

Keywords: *community development; community development corporations; neighborhood; revitalization; interrupted time series; housing prices*

Do efforts by governments, community development corporations (CDCs), or for-profit developers to revitalize distressed, inner-city neighborhoods make any demonstrable difference? Put differently, can a method be devised for persuasively quantifying the degree to which significant, place-based investments causally contributed to neighborhoods' trajectories, compared with what would have occurred in the absence of interventions? This

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challenge to measure the causal impacts of community development initiatives quantitatively has been raised by legislators, foundation program officers, and social scientists alike (Vidal 1992, 1995; Smith 2003). It is of central relevance for a host of contemporary policy initiatives, such as federal and state empowerment and enterprise zones, cities' targeting of Community Development Block Grant and HOME Investment Partnerships Program funds, the U.S. Department of Housing and Urban Development's Jobs Plus demonstration for increasing employment in public housing developments, and a plethora of CDC-driven neighborhood revitalization strategies. Our article responds to this challenge by applying a variant of the well-known interrupted time-series approach (Shadish, Cook, and Campbell 2002) that we believe offers important methodological advantages.

The approach described in this article, which we label the adjusted interrupted time-series (AITS) method, has long been known as a quasi-experimental research design (Campbell and Stanley 1963; Cook and Campbell 1979; Shadish, Cook, and Campbell 2002).[1] To our knowledge, it never before has been operationalized in the context of measuring the impacts of community development initiatives. Its strength is in dealing with the comingled problems that have plagued the ability to draw causal inferences from prior methods, establishing a convincing counterfactual estimation and dealing with neighborhood selection bias, as we explain below. Essentially, the AITS method makes pre- and postintervention comparisons of both the level and slope (collectively what we call the "trend" hereafter) in a target neighborhood outcome indicator of interest. The postintervention measurements are adjusted, however, for extratarget neighborhood factors that affect the outcome indicator in all of the city's low-income neighborhoods, including those that were not targeted for the intervention. Thus, the method makes both pre- and postintervention comparisons within the target neighborhood after taking into account factors that affect the measured outcome in all low-income neighborhoods and so does a much better job in isolating the effect of the targeted intervention on conditions in the impact areas. As such, we believe that the method can, under certain circumstances, offer a powerful tool to program impact evaluators and policy analysts in the realm of community development.

Our article proceeds as follows. We begin by examining the challenges that establishing a counterfactual scenario and neighborhood selection pres-

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ent to program impact evaluators, in the context of reviewing previous approaches to community development impact evaluation. We then present our AITS method, first in a nontechnical, graphic form and then as an econometric model, explaining how it meets these challenges. Next, to demonstrate the method, we apply it to measuring home price impacts in three illustrative cases of large-scale, place-based community development initiatives. Finally, we assess the strengths and limitations of the AITS method in this application and implications of our work.

THE CHALLENGE OF MEASURING IMPACTS OF COMMUNITY DEVELOPMENT INITIATIVES

There are numerous challenges in trying to measure precisely the effects of place-based revitalization initiatives, which have been well documented (Bartik 1992; Baum 2001; Bloom and Glispie 1999; Erickson and Friedman 1989; Fulbright-Anderson, Kubisch, and Connell 1998; James 1991; Mueller 1995; Rossi 1999; Taub 1990; Weiss 1972, 1998).[2] These include the following:

- An intervention may not be discrete and/or may occur in multiple phases, rendering it difficult to delineate precisely pre- and postintervention periods;
- effects may transpire only after a significant lag;
- effects may be difficult to measure, especially if they involve changes in attitudes and expectations;
- the most appropriate indicators of effects may not be obvious or might vary by neighborhood context;
- effects may be produced by synergistic relationships, making attributions to individual causes difficult;
- effects may emanate over space to an extent that does not closely correspond to the boundaries established for the neighborhood under investigation;
- effects may emanate over space to such a wide extent that “control neighborhoods” are inadvertently affected by a distant intervention; and
- people who may accrue the most benefits in target neighborhoods may be most likely to leave the environs, making it difficult to measure full program benefits.

Here, however, we focus on two interrelated problems that relate to what causal inferences can be drawn from whatever is measured. That is, even if all the above problems were absent, inferences about whether a particular intervention caused any demonstrable difference would be challenged by establishing the counterfactual scenario and neighborhood selection bias.

Arguably, the most fundamental challenge in drawing causal inferences about a community development initiative's neighborhood impact is establishing the "counterfactual situation": the patterns of an outcome indicator that would have happened in the neighborhood "but for" the intervention. The counterfactual situation must be accurately estimated because it provides the baseline of comparison against which the actual changes in the neighborhood's indicators get measured to assess the intervention's putative impact. As we demonstrate below, different designs approach the estimation of the counterfactual scenario in quite different ways with, we argue, differing degrees of credibility.

Establishing the counterfactual situation is complicated by the closely related issue of neighborhood selection bias (Rossi 1999). That is, the neighborhoods in which community development interventions occur are likely not a random sample of all urban neighborhoods or even all distressed core community neighborhoods. Some may be targeted for intervention because they have certain strengths that bode well for future development potential, such as proximity to strong neighborhoods, natural amenities, or vibrant anchor institutions; such was the selection rationale of the Empowerment Zone program, for example. Yet, others may be targeted because they are in especially desperate circumstances of need. Still others undertake major community development initiatives because exceptionally able or politically well-connected community-based organizations are present. The upshot is that methods for establishing counterfactual situations must take into account the likelihood that what would have transpired in the absence of interventions in areas targeted for programmatic impacts is not representative and thus not well approximated by patterns in other, "generic" low-income neighborhoods.

Unfortunately, conventional methods of dealing with selection bias are inapplicable here. The usual solution involves either random assignment or a two-stage econometric model of the selection process using instruments that affect selection but not subsequent outcomes. In the case of place-based interventions, random assignment is infeasible, and the modeling approach is thwarted by either small samples of intervention sites and/or a byzantine selection process that is difficult to instrument. What has been tried in the area of community development impacts, as we describe in the next section, deals with the issue in an unconvincing fashion.

ALTERNATIVE METHODS OF ESTABLISHING THE COUNTERFACTUAL SCENARIO FOR COMMUNITY DEVELOPMENT INTERVENTIONS

Although many different labels have been applied to different research designs in the past (Shadish, Cook, and Campbell 2002), we find it helpful to categorize approaches according to three criteria:

- Do they compare indicator values both before and after an intervention?
- Do they use time-series measurements of an indicator (in either period)? and
- Do they observe absolute changes in a target neighborhood only or make comparisons relative to other, comparison ("control") neighborhoods?

Below, we briefly describe various approaches involving permutations of these criteria, provide examples from the community development literature, and point out weaknesses in establishing the counterfactual scenario. We argue that the AITS method, by estimating pre- and postintervention slopes and levels of indicators in a target neighborhood and then comparing them with those in a control set of neighborhoods, offers a preferable specification of the counterfactual situation. To aid the reader, Table 1 summarizes the primary differences among the approaches and cites illustrative examples.[3]

POSTINTERVENTION ABSOLUTE CHANGE APPROACH

This approach examines changes in an indicator transpiring in a neighborhood after some major event has occurred; the direction of change is attributed to the event (Rossi 1999). The counterfactual situation implicit here is that the observed change would not have occurred without the given event. Observations of the positive trajectories of low-income neighborhoods making reputed "comebacks" in the 1990s (typically with the help of CDCs) are representative of this approach (Blank 2000; Grogan and Proscio 2000; Morley 1998; Proscio 2002; Walsh 1997).

POSTINTERVENTION RELATIVE CHANGE APPROACH

In this case, the change (or slope) in an indicator observed in a target neighborhood during the period during which an intervention is reputedly having an impact is compared with analogous changes in one or more control neighborhoods. In this approach, sometimes called "site matching," the counterfactual situation is estimated by events in the control neighborhoods.

TABLE 1: Summary of Alternative Methods of Establishing the Counterfactual Scenario for Community Development Interventions

	Type of Change in Target Area Indicator	
Point of Comparison	*Absolute Change*	*Relative Change*
Postintervention	Change in indicator level or slope in target neighborhood after intervention is observed	Change in indicator level or slope in target neighborhood after intervention is compared with change in level or slope in control neighborhoods (sometimes called "site matching")
	Counterfactual is no change in indicator; assumes that observed change is attributable to intervention	Counterfactual is change in control neighborhoods after intervention; assumes that difference between target neighborhood change and change in control neighborhoods is attributable to intervention
	See Walsh (1997), Morley (1998), Blank (2000), Grogan and Proscio (2000)	See Weiss (1972); Vidal, Howitt, and Foster (1986); Taub (1988, 1990); Mueller (1995); Taylor (2002); Smith (2003); Zielenbach (2003)
Pre- and postintervention	Indicator level or slope in target neighborhood after intervention is compared with level or slope in target neighborhood before intervention	Indicator level or slope in target neighborhood after intervention is compared with level or slope in target before intervention and with changes in control neighborhoods before and after intervention
	Counterfactual is preintervention level or slope; assumes that difference between pre- and postintervention level or slope is due to the intervention	Counterfactual is change in control neighborhoods before and after intervention; assumes that "change in the differences" between target and control neighborhoods before and after intervention is due to intervention
	See Weiss (1972), Rossi (1999), Bloom and Ladd (1982) Bloom (2003)	See Engberg and Greenbaum (1999), Greenbaum and Engberg (2000), Bloom and Glispie (1999)

Thus, only the relative advantages of the target neighborhood over the control neighborhoods after the intervention are taken as evidence of impact[4] (e.g., Weiss 1972; Vidal, Howitt, and Foster 1986; Taub 1988, 1990; Mueller 1995; Taylor 2002; Zielenbach 2003; Smith 2003).

PRE- AND POSTINTERVENTION ABSOLUTE CHANGE APPROACH

Here, analysts contrast measurements of an indicator in a target neighborhood both before and after an intervention; the preintervention value (either the level or rate of change in the indicator) is assumed to be the counterfactual scenario (Weiss 1972). The measurement can be based on just one observation each before and after the intervention or many observations at short intervals before and after an intervention, permitting an interrupted time-series analysis (Rossi 1999). Contrast the approaches of Taub (1990) and Bloom (2003), which use few observations, with that of Bloom and Ladd (1982), which uses many.

PRE- AND POSTINTERVENTION RELATIVE CHANGE APPROACH

Recently an approach has been used that merges the prior two: pre- and postintervention change (either level or rate) in an indicator in a target neighborhood is compared with the analogous change in control neighborhoods before and after an intervention. In this approach, the counterfactual situation is the changes in control neighborhoods before and after the intervention; only inasmuch as the change in the target neighborhood differs from that in the control neighborhoods will an impact be registered. There are three versions of this approach in the literature, distinguished by the frequency of observations made before and after interventions (Bloom and Glispie 1999). Some evaluations use only one observation in each period, thus in effect comparing pre- and postintervention differences in levels of an indicator between intervention and nonintervention sites. Others use trends established with only two observations before and after interventions, such as those of Engberg and Greenbaum (1999) and Greenbaum and Engberg (2000). Bloom and Glispie offer another approach with frequently recurring observations that permit a richer, comparative interrupted time-series analysis.

OUR APPROACH: THE AITS METHOD

Our approach builds on the logic of the pre- and postintervention relative change approach but adds one important enhancement: Not only the slope but also the level of an outcome indicator is compared intertemporally and cross-sectionally. As explained in the next subsection, this seemingly minor modification offers significant advantages for reducing the ambiguity of the counterfactual scenario. Our AITS method estimates the counterfactual scenario in two steps. First, we extrapolate from the level and slope of our indicator (estimated from frequently, sometimes simultaneously recurring data on home sales) in the area affected by an intervention into the period after the intervention. Second, we adjust this extrapolation for postintervention changes in indicator levels and slopes in all other low-income neighborhoods to control for forces not associated with the intervention that may have larger scale effects in other neighborhoods with similar socioeconomic conditions.

To illustrate, suppose that in a city under investigation, we observe that our outcome indicator, home prices in this case, is rising at 1% annually in the area that we know from hindsight will be the target of a future community development intervention. By comparison, comparable homes in other low-income neighborhoods in the city are selling from a base that (at some baseline date) is 10% higher, and prices are rising at 2% annually. In the years following the intervention under investigation, suppose that prices in the impact area (controlling for any differences in homes sold) jump immediately to a base that is 5% higher than originally in the impact area and then rise 6% annually on average, whereas those of comparable homes in other low-income neighborhoods rise 3% annually. Now, our counterfactual estimation in the impact area would start by extrapolating the 1% growth from a low base level into the postintervention period. But, recognizing that prices in other low-income neighborhoods rose 1% faster during this period than they had previously (for reasons with which we need not concern ourselves), this should also apply to our impact area. So, our counterfactual scenario is 2% annual growth in prices in our impact area that would be predicted in the absence of intervention. Because the actual growth in the impact area was 6% annually, we attribute to the intervention the 4% difference in appreciation rates. Of course, the shifting up the postintervention level of prices by 5% immediately after the intervention also is included as an additional effect.

Thus, our AITS approach can be thought of as equivalent to a "difference-in-differences" model.[5] In the preintervention period, the differences between the target and control neighborhood indicators were –10% in level and –1% in appreciation rate; after the intervention, the differences changed to –5% in level and +3% points in appreciation rate. Because the difference in the differences changed to favor relatively the impact area in both the level and appreciation of the indicator, this hypothetical situation demonstrates a positive effect of the intervention.

THE COMPARATIVE ADVANTAGES OF THE AITS APPROACH

We can demonstrate with the help of some hypothetical graphic illustrations the comparative advantages of the AITS approach over other methods for establishing the counterfactual scenario in community development impact evaluations. Consider first Figure 1. It portrays hypothetical values over time for some desirable outcome indicator of interest in two sorts of geographic areas in a city under investigation. One is the "control area," consisting of low-income neighborhoods where no major community development initiatives are targeted during the period.[6] The other is the "target area," where the initiative under study will commence at a time denoted by the vertical dashed line. Assume that control area trends in the indicator are as shown by C-C′-C″; the trend break implies that some new forces affecting all low-income neighborhoods in the city began impinging at the time corresponding to the break. Also assume that the area targeted for the initiative starts with a lower level of the indicator (A vs. C) than control areas but changes at the same rate (i.e., A-A′ parallels C-C′). This indicates that the impact area, even before the intervention, had time-invariant indicator values that were well below those of the control area (indicating, perhaps, a local disamenity), even though the rate of change over time before the intervention was the same in both the intervention and control areas.

We have argued that the preferred specification of the counterfactual scenario in the target area is line A′-A″: the projection of the preintervention slope in the target area, adjusted for control area changes in slopes (i.e., the break between C-C′ and C′-C″) coincident with the pre- and postintervention periods. Put differently, the correct test of whether a community development initiative has an effect is whether there is a pre- and postdevelopment break in the slope (and/or shift in level) in the impact neighborhood indicator, which is different than what was observed in the control areas. In effect, A′-A″ is the counterfactual scenario for the impact area; it assumes that the rate of change in the indicator for the impact area would be identical as the rate of change in the control area, albeit on a lower base, created by the local disamenity.

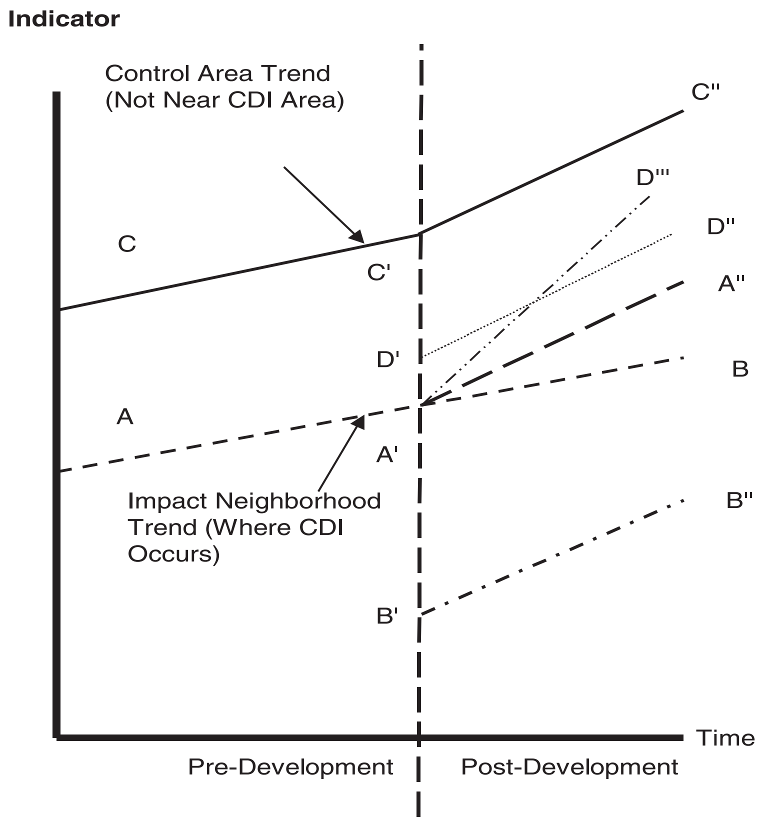

Figure 1: Illustration of Potential Types of Neighborhood Impacts From Community Development Initiatives

NOTE: Positive impact, absolute increase in trend: A-A′-D′′′. Positive impact, absolute upward shift in level: A-A′-D-D″. No impact, no relative change in trend from control area trend: A-A′-A″. Negative impact, relative decrease in trend: A-A′-B. Negative impact, absolute downward shift in level: A-A′-B′-B″. CDI = community development initiative.

Thus, were we to estimate empirically line A-A′-A″, this would signify no impact, because the indicator slope break after the initiative mirrored the slope break observed in control neighborhoods (line C-C′-C″). However, if the indicator in the impact neighborhood after the initiative were to shift up to a higher level (e.g., A-A′-D′-D″) and/or increase more rapidly than the control area slopes (A-A′-D′′′), this would signify a positive impact. Conversely, if the indicator in the impact neighborhood after the initiative were to shift down to a lower level (A-A′-B′-B″) and/or increase less rapidly (decrease

TABLE 2: Summary Interpretations of Implied Impact of Intervention on the Basis of Alternatives Portrayed in Figure 1

Impact Neighborhood Trend Line	*Comparison of Impact and Control Neighborhood Trend Lines*	*Impact Finding*
A-A′-D‴	Increase in slope relative to slope of control area C-C′-C⁗; reflects acceleration in target area slope relative to control area	Positive impact
A-D′-D″	Increase in level relative to level of control area at C′; reflects upward shift in indicator value relative to control area	No impact
A-A′-A″	No change in slope or level relative to control area trend C-C′-C″	
A-A′-B	Decrease in slope relative to control area C-C′-C⁗; reflects lag of target area slope relative to control area	Negative impact
A-B′-B⁗	Decrease in level relative to control area at C′; reflects downward shift in indicator value relative to control area	

more rapidly) than the control area slopes (A-A′-B), this would signify a negative impact. These arguments are summarized in Table 2.

Contrast these conclusions to those that would have been produced from the approaches represented in the community development literature thus far. The postintervention absolute change approach would have erroneously concluded positive impacts if any of the target area indicator profiles shown were manifested, because all postintervention slopes were upward. The postintervention relative change approach would have erroneously concluded no impacts if either target area indicator profile D′-D″ or B′-B″ were manifested, because the slopes were identical to those in control areas. The pre- and postintervention absolute change approach would have erroneously concluded a positive impact if A-A′-A″ were manifested (because the target area slope break was positive) and no impact if A-A′-B were manifested (no change in target area slope).

In the case of the pre- and postintervention relative change approach, the critique depends on whether there are sufficient observations to establish indicator slopes both before and after an intervention or only an observed level. Pre- and postintervention comparisons of levels alone may obscure significantly different slopes before and after an intervention, thereby leading to

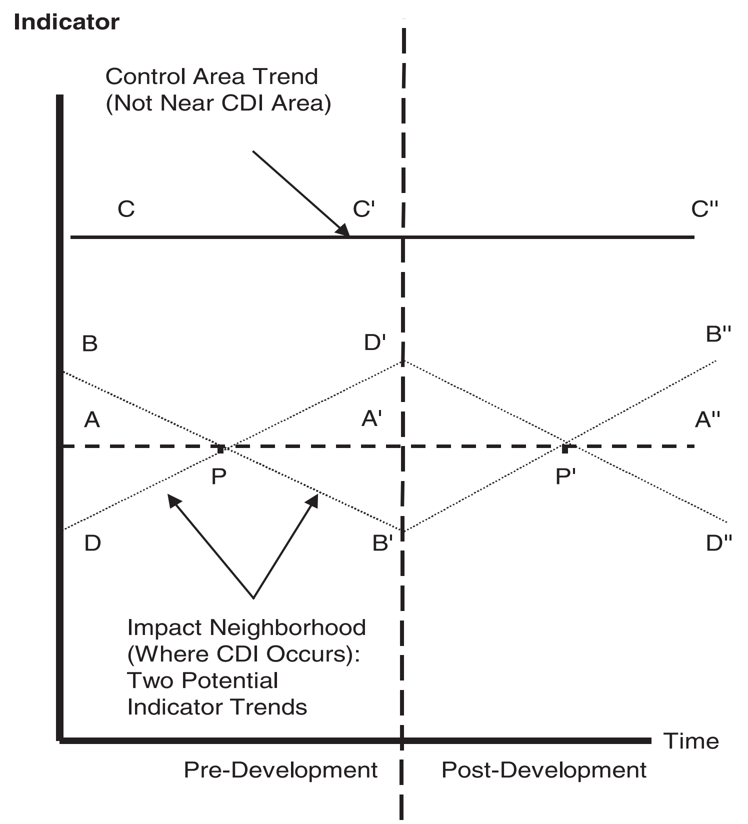

Figure 2: Illustration of Potential Types of Neighborhood Impacts From Community Development Initiatives (Pre- and Postintervention Levels of Indicator Method Critique)

NOTE: Positive impact, absolute increase in trend: B-B′-B‴. Negative impact, absolute decrease in trend: D-D′-D″. CDI = community development initiative.

erroneous conclusions. Our argument is illustrated with the help of Figure 2. Assume for simplicity that during the period in question, there is no change in the indicator in control areas (line C-C′-C″). But suppose that we also observe points P and P′ and thereby deduce no change between pre- and postintervention periods in the average level of the indicator in the impact neighborhood. Now only if the true, underlying slope in the impact neighborhood were A-A′-A″ would this method's deduction of no impact be correct. As illustrated in Figure 2, such an observation of points P and P′ might well be consistent with quite different types of pre- and postintervention slope breaks, suggesting either strong positive (line B-B′-B″) or negative (line D-D′-D″) impacts.

If, on the other hand, data were sufficient for estimating slopes before and after the intervention, the pre- and postintervention relative change approach produces the correct counterfactual scenario but a potentially biased empirical measure of impact. The problem arises through using an econometric specification permitting only a pre- and postintervention change in the slope, excluding a potential shift in the intercept at the intervention time. Referring to Figure 1, suppose the true values of the indicator are shown by segments A-A′ and D′-D″, suggesting a discontinuous (but ongoing) fillip of D′-A′ amount of the indicator, but no greater rate of change in the impact neighborhood as in control areas. A specification that forces a splinelike break in the estimated line at point A′ would produce, however, a segment such as A′-D‴, which clearly overstates the rate of increase in the indicator and, hence, the positive impact measured. In sum, the AITS method avoids the potential shortcomings of the pre- and postintervention relative change approach by estimating the slopes and levels of the indicator in both the target and control areas both before and after the intervention, adjusting the former as appropriate for changes in the latter to establish the counterfactual situation.

THE AITS MODEL IN ECONOMETRIC TERMS

THE BASIC MODEL

Our basic AITS regression specification may be expressed symbolically as

$$\begin{aligned} I_t = c &+ (d \times \mathrm{DIMP}_t) + (e \times \mathrm{DPOSTIMP}_t) + (f \times \mathrm{TRIMP}_t) + \\ &(g \times \mathrm{TRPOSTIMP}_t) + (h \times \mathrm{TRALL}_t) + \\ &(j \times \mathrm{TRPOSTALL}_t) + (k \times [\mathrm{SPACE}]) + \varepsilon, \end{aligned} \tag{1}$$

where I is the indicator of the program intervention outcome of interest; c is a constant term; DIMP is a dummy denoting the impact area, equal to 1 for pre- and postintervention observations and 0 otherwise; DPOSTIMP is a dummy denoting the impact area, equal to 1 for postintervention observations only and 0 otherwise; TRIMP is the slope variable for the indicator in the impact area both before and after the intervention, equal to 1 for observation of the impact area during the first period (month, quarter, or year) of study, 2 for observation of the impact area during the second period of study, and so on, and 0 otherwise; TRPOSTIMP is the slope variable for the indicator in the impact area only after the intervention, equal to 1 for observation of the impact area during the first period (month, quarter, or year) of study after the intervention, 2 for observation of the impact area during the second period after intervention, and so on, and 0 otherwise; TRALL is the slope variable for indicator in all low-income areas (including the target area) both before and after the intervention, equal to 1 for observation of a low-income area during the first period of study, 2 for observation of a low-income area during the second period of study, and so on, and 0 otherwise; TRPOSTALL is the slope variable for the indicator in all low-income areas (including the target area) during the postintervention period only, equal to 1 for observation of a low-income area during the first period of study after the intervention, 2 for observation of a low-income area during the second period after the intervention, and so on, and 0 otherwise; [SPACE] is a vector of spatial autocorrelation and heterogeneity correction variables (Can 1997; Can and Megbolugbe 1997; see below); and ε is a random error term with statistical properties discussed below.

All lowercase letters in the equation (b, c, d, etc.) represent coefficients to be estimated. The subscript t denotes a time period for which an indicator is measured. For AITS, this typically is monthly or quarterly; here, it is whenever a home sells.

The AITS model deals with the neighborhood selection bias challenge by permitting both the level and the slope of an indicator in the impact area to differ from that of the generic low-income neighborhood prior to any intervention. The statistical significance of the d coefficient is equivalent to testing for a difference in the preintervention levels of the indicator in the impact and control neighborhoods, or the difference between C and A in Figure 1; the statistical significance of the f coefficient is equivalent to testing for a difference in the preintervention slopes of the indicator in the impact and control neighborhoods, or the difference between the slopes of lines C-C′ and A-A′ in Figure 1. Because these potentially idiosyncratic, preintervention impact area levels and slopes are modeled explicitly as a basis for estimating a postintervention counterfactual scenario, the selection bias challenge is overcome.[7]

The test for the statistical significance of the coefficient e of the DPOSTIMP variable is equivalent to testing that there is a discontinuous, time-invariant change in the indicator levels in the impact neighborhood after the intervention, as would be the case if there were a shift in the impact area from A′ to C′, as shown in Figure 1. The size of e provides the quantitative estimate of impact. The test for the statistical significance of the coefficient g of the TRPOSTIMP variable is equivalent to testing that there is a change in the indicator slopes in the impact area, as would be the case, for example, if the slope of the line A′-A″ in Figure 1 changed to A′-D‴. The product of *g* and the TRPOSTIMP variable provides the (time-dependent) magnitude of impact. Should both the shift and slope postintervention coefficients prove to not be significantly different from zero, it would reject the hypothesis of impact.

We stress that the results of any regression model do not offer conclusive proof of causation, merely association. Nevertheless, the AITS specification, by clearly comparing pre– and post–announcement of intervention differences in indicator levels and slopes (adjusted for changes in control area slopes), provides exceptionally convincing evidence in this regard.

ECONOMETRIC ISSUES

In this application of measuring community development impacts, we analyzed large samples of home sales that occur at widely varied locations across a city and moments across a multiyear period. As such, it becomes a special application of a conventional "hedonic index model," the econometric dimensions of which have been developed over a long period (e.g., Goodman 1978; Clapp, Pace, and Rodriguez 1998; Smith 2003).[8] First, ε in equation 1 may be subject to spatial autocorrelation that, if left uncorrected, would lead to biased parameter estimates and misleading *t* tests. To test for this potential problem, we used a specification that Can and Megbolugbe (1997) found to be robust. We calculated the spatial lag of the indicator variable we report in this article (home sale prices) and included it in our model as an independent variable. The spatial lag is a spatially weighted average of all of the observations of the dependent variable within a certain distance from the reference observation. Consistent with the approach of Can and Megbolugbe, we used the inverse of the distance ($1/d$) as the spatial weight. The formula for the spatial lag is

$$\text{Spatial Lag}(P_i) = \Sigma_j[(1/d_{ij})/\Sigma_j(1/d_{ij})]P_j\,, \tag{2}$$

where P_i is the value of the home sale for which we are calculating the spatial lag, d_{ij} is the distance between sales *i* and *j*, and P_i is one of the set of all sales within distance *d* of P_j that occurred within the 6 months prior to the date of P_i. We tested spatial lags with *d* cutoffs of 2,000, 5,000, and 10,000 feet to examine the possibility that spatial dependence may exist over a larger area.

Because of the large number of house sales in the sites investigated, calculating the spatial lag for this indicator variable is extremely intensive computationally. To see if this was justified, we conducted several preliminary tests of spatial lags estimated for various distances using only sales in a contiguous subset of census tracts. We found that no variant of the spatial lag was statistically significant or substantially improved the goodness of fit (R^2) of the preliminary models, and we therefore excluded it from the final models reported here. We stress that this is not necessarily a general conclusion; rather, we believe that our inclusion of census tract fixed effects essentially performed the function of a spatial lag.

A second econometric issue is spatial heterogeneity, sometimes known as spatial submarket segmentation, which refers to the systematic variation in the behavior of a given process across space. Here, the issue is whether the parameters of equation 1 are invariant across space or whether they assume different values according to the local socioeconomic, demographic, and/or physical contexts of the various neighborhoods constituting the geographic area under study. If such were the case, the error term ε would be heteroskedastic.

To deal with this issue, we used the "spatial contextual expansion with quadratic trend" specification, as suggested by Can (1997). This method involves adding to the models the latitude (x) and longitude (y) coordinates of each observation in the following variables (normalized so that zero values represent the center of the city): x, y, xy, x^2, and y^2. Higher numerical values of x (y) signify increasing distance from the center of the city heading west (north). These variables typically proved statistically significant in our specifications, suggesting that our various controls for local fixed effects needed further supplementation from these spatial coordinates. They may be interpreted as broad home price gradients measuring accessibility to jobs, amenities, or disamenities affecting wide swaths of cities.

In addition to the aforementioned spatial econometric tests, standard heteroskedasticity tests using the Goldfeld-Quandt and other procedures were conducted (Intriligator 1978:156). Although they proved inconclusive, to be conservative, we used White's (1980) covariance matrix to estimate the standard errors reported here.

AN APPLICATION OF THE AITS METHOD: HOME PRICE IMPACTS OF COMMUNITY DEVELOPMENT INITIATIVES

To test a prototype of the AITS model, we applied it in an impact analysis of neighborhood home price impacts from three purposively sampled, large-scale community development initiatives, each of which had CDCs as major drivers. These are summarized in Table 3. This section provides details of our particular modifications of the generic AITS model described in equation 1 above, brief summaries of each initiative, followed by results.

OVERVIEW OF OUR IMPACT ANALYSIS

As part of a comprehensive qualitative and quantitative study of the impacts of CDC-led community reinvestment initiatives, we used the AITS method, with the sale prices of single-family homes as the indicator. Although home prices are certainly not the only appropriate indicator one might consider, they have been used often inasmuch as numerous factors contributing to a neighborhood's quality of life will be capitalized into property values (Grieson and White 1989; Palmquist 1992; Polinsky and Shavell 1976). We obtained home sales data from local deed records purchased from Experian, a vendor. Addresses were geocoded so sales could be identified with particular neighborhoods. We obtained sufficient data so that several years' worth of sales both before and after the intervention were represented.[9] Executive directors of CDCs and other key local informants were consulted to obtain information about the timing, nature, and spatial extent of community development initiatives in the neighborhood of interest, so that impact areas and pre- and postintervention periods could be established.

In our version of equation 1, each home sale constituted a unit of observation. To improve its accuracy as a market-based indicator of neighborhood quality of life, we standardized homes sold by controlling for a large number of their structural characteristics and area-invariant fixed effects in the context of equation 1.[10] The natural log of home price served as the dependent variable. TRALL was operationalized as a set of year-quarter dummy variables to permit the richest possible variation in the overall level of home prices in each city. Equation 1 was generalized to test not only for pre- and postintervention changes but also those associated with an "interim period" as well, during which key construction projects were under way.[11] We denote these variables using the INT acronym instead of POST. We estimated potential effects over the "impact area," which consisted of the multiple contiguous blocks where the initiative was concentrated and all adjacent blocks; details are provided in the maps that follow.[12]

BELMONT NEIGHBORHOOD, PORTLAND, OREGON

Once a bustling area around a trolley line terminal, by the late 1980s, the Belmont commercial corridor in southeast Portland had degenerated into a mix of empty buildings, industrial establishments, and a few bars and shops

TABLE 3: Summary of Study Neighborhoods, Strategy, and Program Interventions

City/Neighborhood/ CDC	*Demography*	*Preintervention Condition*	*General CDC Strategy*	*CDC Programmatic Interventions*	*City/Private Investments*
Boston, Massachusetts/ Jamaica Plain/JPNDC	8,000 residents, Latino, African American, with Whites in-migrating	Improving, with gentrification Significant blight in Hyde-Jackson Square	Comprehensive housing, commercial, social services, community organizing	Made major investments in multifamily rehabilitation and new shopping center development in Hyde-Jackson Square	New light rail stop in early 1990s Scattered private investment in mid-1990s
Denver, Colorado/ Five Points/HOPE Communities	8,000 residents, with older Blacks and in-migrating Latinos and Whites	Stable low-income Declining commercial district, some upgrading	Housing, community organizing, individual empowerment programs	Major multifamily building renovation in neighborhood gateway location	New light rail line Private commercial redevelopment Demolition of troubled public housing
Portland, Oregon/ Belmont/REACH Community Development, Inc.	8,000 residents, predominately White	Improving, with gentrification Deteriorated commercial district	Area-tailored housing, commercial redevelopment, community planning, social services, community organizing	Extensive Main Street program in centrally located commercial strip	Industrial plant conversion to large, mixed-use development during interim period

NOTE: CDC = community development corporation; JPNDC = Jamaica Plain Neighborhood Development Corporation.

(see the map in Figure 3). A large, vacant, and deteriorated dairy building was a significant source of blight and had become a haven for drug dealing, further discouraging the active patronage of neighborhood business. But in the early 1990s, spurred by sharply increased demand for architecturally interesting, even if run-down, Victorian homes near downtown, housing prices in the neighborhood began to rise at an annual pace equal to or exceeding that of Portland as a whole. But the resurgence of residential markets bypassed the commercial corridor, which continued to suffer vacancy rates of 20% to 25%. The redevelopment problem was how to turn around a blighted retail strip in the midst of an improving residential neighborhood.

Incorporated by a group of housing advocates in 1982, REACH Community Development, Inc., began as an affordable housing developer active in seven southeast Portland neighborhoods. The organization soon grew to take on a range of other activities, including economic development, community organizing and leadership building, and social services, including tutoring and summer programs and service referrals for special-needs populations living in REACH housing.

In the early 1990s, REACH initiated a new approach to community revitalization, which involved the creation of targeted redevelopment strategies for specific subareas within southeast Portland. These strategies would be designed and carried out by neighborhood organizations and community leaders, with supporting investments made by REACH. As its second such program, REACH selected a five-by-twelve-block area centering on the Belmont Street business district. Three years after choosing Belmont, REACH was ready to go to work on residential properties in the area, but by then, housing had become less affordable, and REACH switched to the commercial corridor as its redevelopment priority.

In partnership with the Belmont Business Association, REACH developed a commercial revitalization plan that called for multiple and simultaneous investments by neighborhood businesses. Under the plan, REACH and its community partners made improvements to commercial facades, upgraded signage, coordinated business marketing (including a business directory), improved safety through better lighting and heightened security, and held workshops on business development on such issues as marketing. To help prevent the loss of long-time businesses as improvements pushed rents to unaffordable levels, REACH initiated a program to encourage business owners to take long-term leases and even purchase property.

The dairy plant renovation by a private developer may have been the clearest outward sign of improvement in the Belmont neighborhood. The dairy became mixed-income housing and space for small businesses oriented to the middle to high end of the neighborhood market. The project and

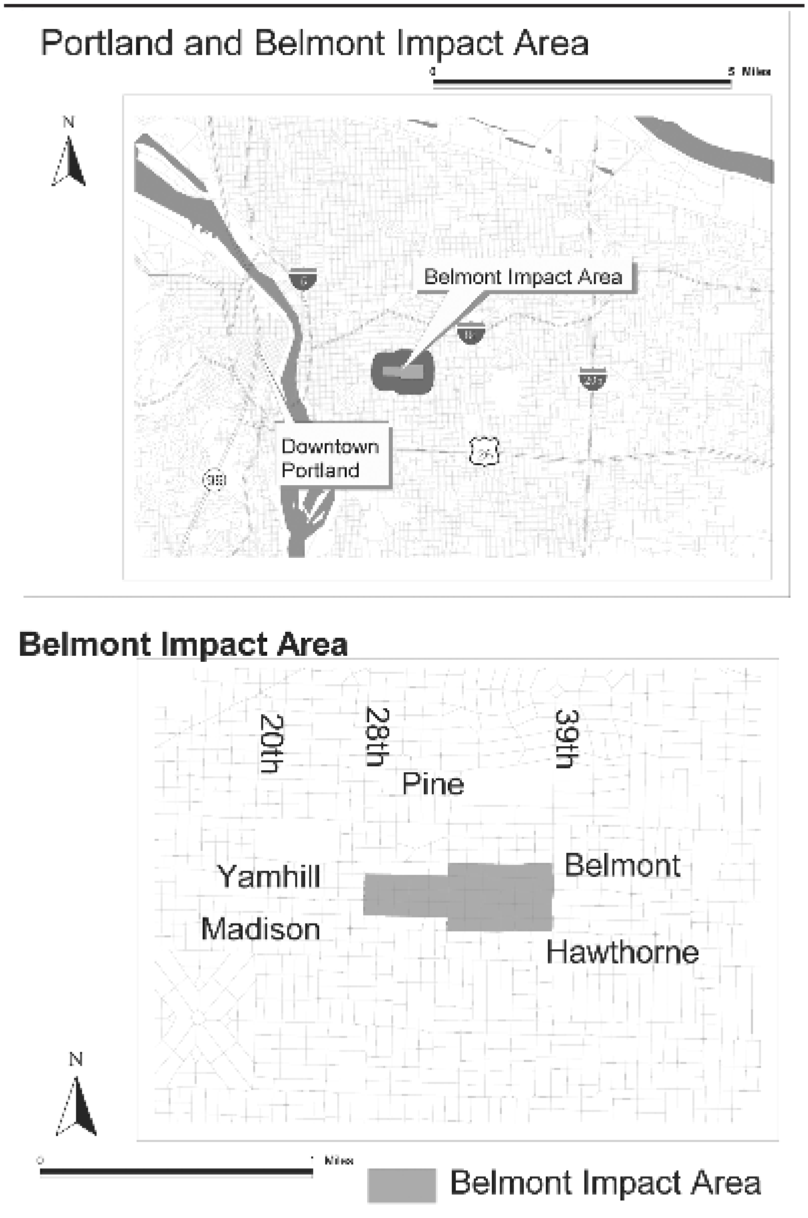

Figure 3: Portland and Belmont Impact Area

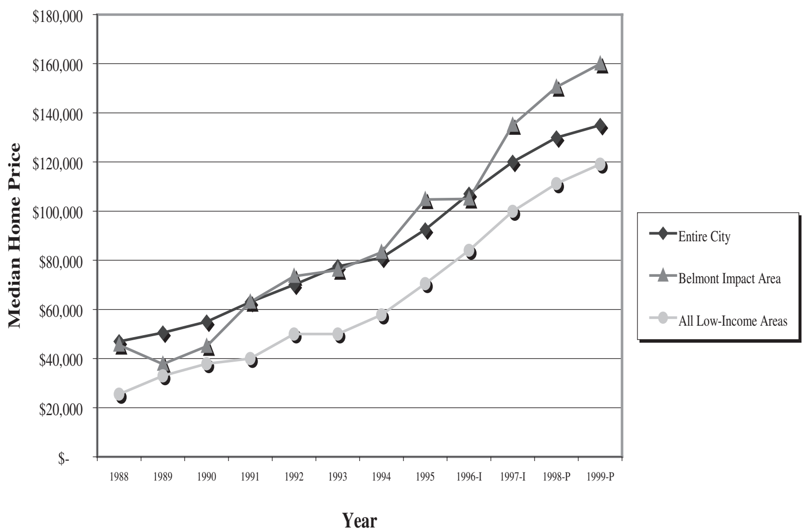

Figure 4: Property Value Changes in the Belmont Impact Area, Portland Low-Income Neighborhoods, and the City of Portland

NOTE: An "I" appended to any year denotes the interim intervention period, and a "P" denotes the postintervention period.

complementary improvements by REACH and its partners arguably induced new businesses to locate on Belmont Street, creating a vibrant, pedestrian-friendly corridor with a number of cafes, restaurants, theaters, and other businesses. This commercial redevelopment area was defined as the core of our potential impact area (see Figure 3).

In this case, even a cursory analysis of home prices in the impact area corroborates these claims; consider the statistics portrayed graphically in Figure 4.[13] Prior to the intervention, median home prices in REACH's development area in Belmont tracked closely the trends in other low-income neighborhoods and those in Portland as a whole. Prices in the development area increased sharply at the end of the interim intervention period, as major portions of the commercial redevelopment effort were completed. This price increment was not observed in other low-income Portland neighborhoods or higher income ones.

AITS analysis of changes in impact area property values relative to other Portland low-income neighborhoods provides even more convincing, precise evidence of REACH's favorable impact. Parameters estimated by ordinary least squares, with econometric adjustments noted above, are presented in the appendix; for brevity, we do not present the coefficients of numerous control variables for home characteristics, quarter-year, census tract, and spatial heterogeneity. As shown in Figure 5, summarizing the econometric results in graphic terms, single-family home prices in the impact area were statistically identical to those in other low-income Portland neighborhoods prior to the REACH program and the dairy renovation (i.e., the DIMP and TRIMP coefficients were not significant; see the appendix). By the start of the interim period, when REACH established its planning process and implemented concrete improvements on the commercial strip, home buyers began to pay a 36% premium for homes nearby (see DINTIMP in the appendix and the corresponding jump in average sales prices during the interim period shown in Figure 5). This premium increased yet again, to 130% (see DPOSTIMP in the appendix),[14] after the intervention was completed, clearly capitalizing powerful aftereffects of REACH's revitalization efforts and the completed dairy renovation.

Note that this finding illustrates the importance of a specification such as equation 1, which allows both the level and the slope of an indicator to vary over time in the impact area. Had an econometric model such as equation 1 omitted DPOSTIMP in the Belmont case, a positive coefficient would have been estimated for the TRINTIMP and/or TRPOSTIMP trend variable, suggesting that the rate of price appreciation was augmented in the impact area because of the intervention. This is contrary to our finding that only the base level of prices, not their relative appreciation, was affected. This is important, because a positive slope finding implies that price increases continue over time and so compound. Our findings in Portland, however, suggest that the neighborhood improvements resulted in a onetime boost to property values, representing the capitalized benefits of a more attractive commercial district nearby.

FIVE POINTS NEIGHBORHOOD, DENVER, COLORADO

Five Points is a loose collection of smaller neighborhoods on the near north side of Denver's downtown, each with its own population characteristics and type of housing stock; see the maps in Figure 6. During the 1950s, Five Points was a populous and busy African American neighborhood. But throughout the 1960s and 1970s, businesses and residents left the neighborhood for the newly integrated suburbs, leaving behind a neighborhood marred by abandoned buildings; vacant land; active open-air drug markets; and a large, distressed housing project in nearby Curtis Park.

Despite deterioration, Five Points had development assets on which to build. Proximity to downtown and an architecturally attractive, if run-down,

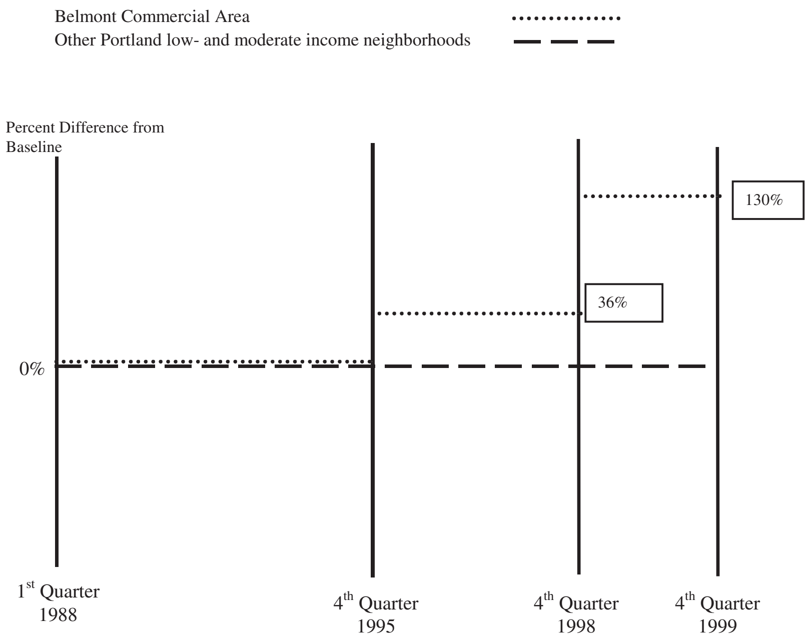

Figure 5: AITS Analysis of Property Value Change in Belmont Impact Area Compared With All Other Portland Low-Income Areas

NOTE: Lines indicate property value differences relative to other low- and moderate-income neighborhoods in the city of Portland (the baseline) after controlling for the quality of properties sold and general economic effects.

older housing stock created circumstances ripe for an upswing in residential markets. The business district, however, remained run down, as did many neighborhood residential properties. Even so, rising housing values and an influx of higher income Whites and moderate income Latinos aggravated racial tension, and business owners on Welton Street, thought to be the "only Black-owned [commercial] strip in the nation," feared displacement by White-owned businesses. The redevelopment problem was how to create affordable housing for those at the lower end of the income ladder in ways that would remove sources of blight, demonstrate the neighborhood's potential for improvement, and contribute to the revitalization of the community's commercial-retail area.

HOPE Communities, a faith-based CDC incorporated in 1980, acquired its 1st low-income property in that year and implemented several other rental and homeowner assistance projects over the decade. It since has developed 11 residential properties with 425 units, housing very low income and largely

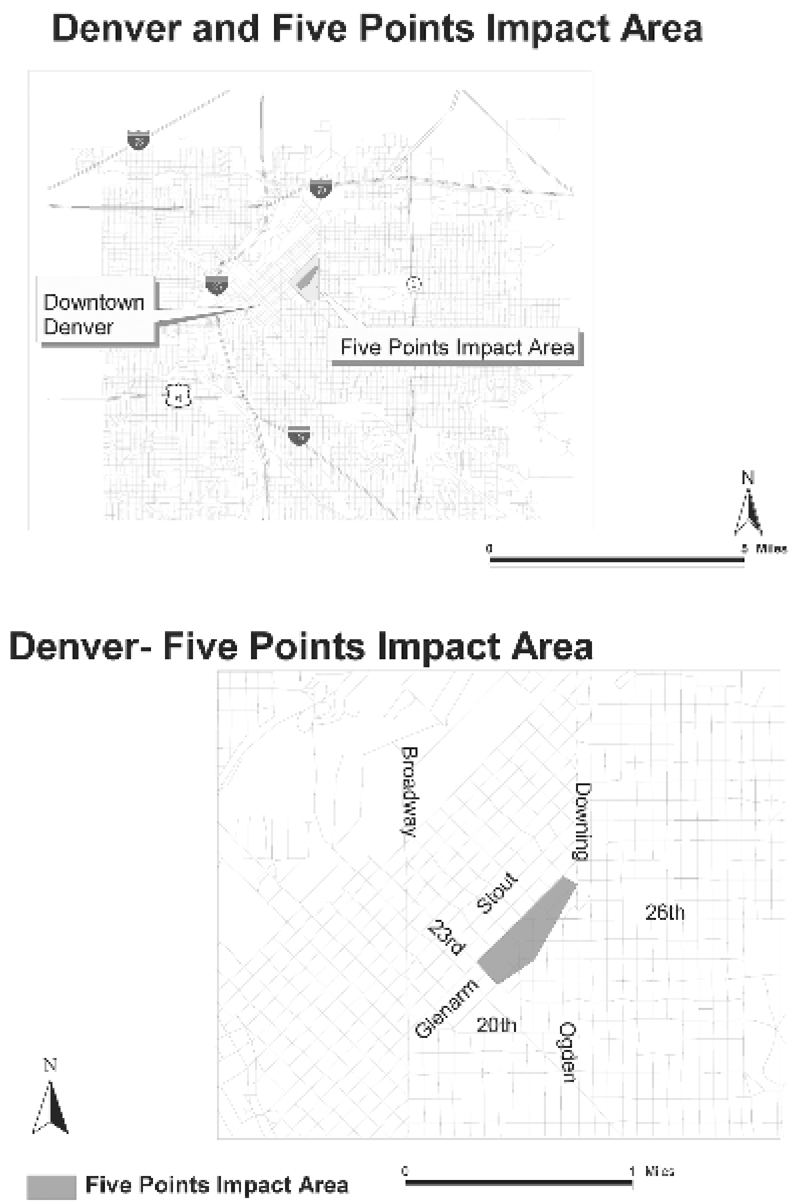

Figure 6: Denver and Five Points Impact Area

African American families. In the late 1980s, HOPE purchased two large, deteriorated garden apartment properties at highly visible neighborhood locations. Selective demolition followed by rehabilitation and infill construction began on Sunnyside Apartments in 1988 and on Carolton Arms in 1990. Several significant, complementary investments came on line about the same time as these CDC developments were finished, including a new light rail transit line through the commercial strip and several city- and privately funded commercial property improvements. Correspondingly, we defined the impact area as the portion of the commercial strip where HOPE's two major residential projects and these other infrastructure investments are located.

Cursory examination of price trends presents an ambiguous picture of impact here. As Figure 7 shows, median home prices in the impact area increased from $40,000 at the beginning of the intervention in 1989 to nearly $60,000 four years after its completion in 1996, though they still remained below prices in other low-income neighborhoods in other parts of Denver. Moreover, it is unclear from Figure 7 whether postintervention price trends in the impact area generally outstripped those in other low-income neighborhoods. Any implications about impact are further clouded by the relatively inferior performance of prices in the Five Points impact area before the intervention and during the first 2 years of construction.

The AITS results, presented in the appendix and portrayed in Figure 8, however, show a much clearer picture. After accounting for factors that may have influenced price trends in all Denver low-income neighborhoods and controlling for differences in the homes that sold, Five Points' property values remained 20% below those in other low-income neighborhoods until the intervention was completed.[15] This is understandable, inasmuch as many of the construction projects were highly disruptive of retail and vehicular traffic. Subsequently, home prices in the Five Points impact area appreciated in relative terms more than 5% per quarter more than similar homes selling in other low-income Denver neighborhoods. This strongly supports claims of a positive impact of considerable magnitude.

JAMAICA PLAIN, BOSTON, MASSACHUSETTS

During the late 1980s and early 1990s, parts of Jamaica Plain, most notably Hyde-Jackson Square, served as a haven for drug dealing and violent crime, and a large concentration of vacant lots attracted undesirable activity (see the maps in Figure 9). Despite this deterioration, the neighborhood remained attractive to a diverse group of residents. It was home to the largest

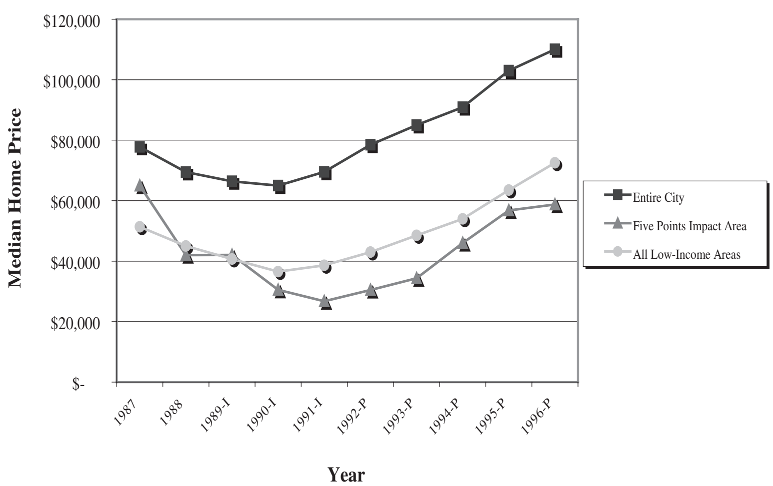

Figure 7: Property Value Changes in the Five Points Impact Area, Denver Low-Income Neighborhoods, and the City of Denver

NOTE: An "I" appended to any year denotes the interim intervention period, and a "P" denotes the postintervention period.

Latino population in New England as well as a substantial African American population, many living in the Bromley Heath public housing project. Jamaica Plain had a significant White ethnic and a growing gay and lesbian population. Some interviewees pointed to neighborhood divisions, symbolized by the Centre Street boundary between the "White side" and the "minority side" of Jamaica Plain. The redevelopment problem was how to promote affordable housing while simultaneously encouraging improvement to neighborhood physical and economic vitality.

Formed in 1977, the Jamaica Plain Neighborhood Development Corporation (JPNDC) grew out of protest around urban renewal and accelerating disinvestment in Boston's southwest corridor. In the early years, JPNDC focused on housing rehabilitation, broadening out in the mid-1980s to include a range of economic development activities. In the early 1990s, JPNDC conducted a strategic planning process that led it to a focus on Hyde-Jackson Square, the target of our impact study.

From 1990 to 1994, JPNDC undertook an investment program consisting of three major projects. First, the redevelopment of abandoned housing and vacant lots on Walden Street, a well-known drug market, created the Hyde Square Co-op, completed in 1994 and owned by 43 low-income families. Second, 10 smaller buildings were refurbished, supported by the Local

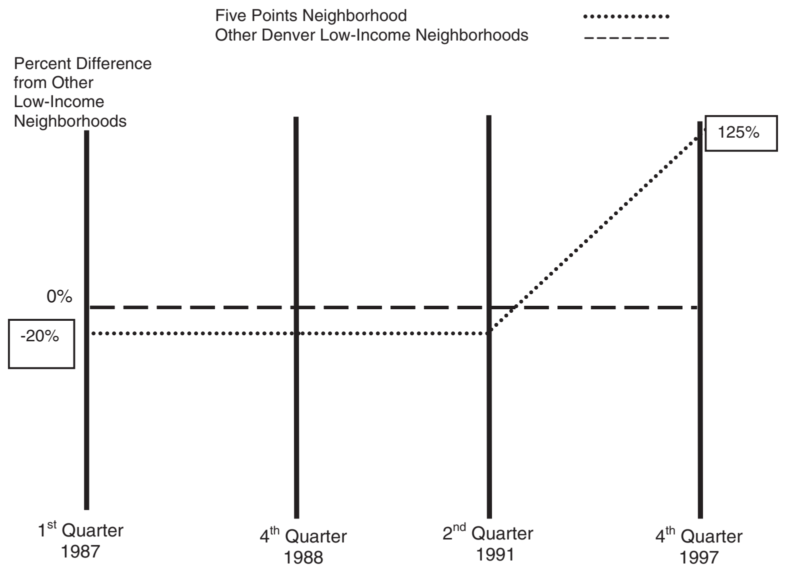

Figure 8: AITS Analysis of Property Value Change in Five Points Impact Area Compared With All Other Denver Low-Income Areas

NOTE: Lines indicate property value changes relative to other low-income neighborhoods in Denver after controlling for the quality of properties sold and general economic effects.

Initiatives Support Corporation. Third, a block centered on an old brewery was rehabilitated. Accordingly, we specified the preintervention period as 1988 through early 1990; the interim period ran from the time of initial planning for the Hyde Square Co-op (the first quarter in 1990) to its completion 4 years later. The postintervention period started in the first quarter of 1994. Our impact area included all the aforementioned developments and their immediate environs (see Figure 9).

JPNDC was widely viewed by local informants as sparking investment in Jamaica Plain through its carefully planned projects, developed with strong business and resident involvement. Local observers reported significant changes in the neighborhood in the mid-1990s, as investors, including JPNDC, began to renovate derelict Hyde-Jackson Square buildings; there were claims that this led to sharply improved property values by the end of the decade.

Indeed, a cursory view of the price trends portrayed in Figure 10 lends credence to the notion of a positive impact. JPNDC impact area median prices fell to a low of $45,000 during 1992, considerably below prices in compara-

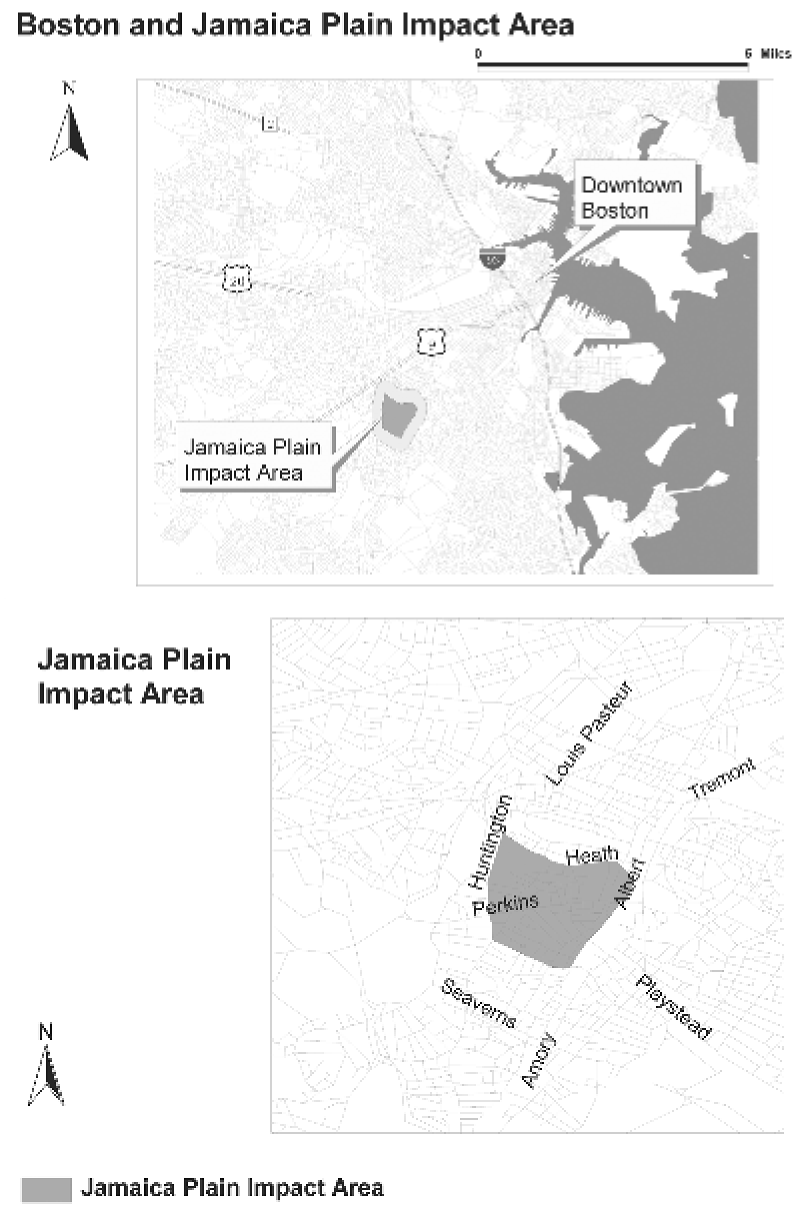

Figure 9: Boston and Jamaica Plain Impact Area

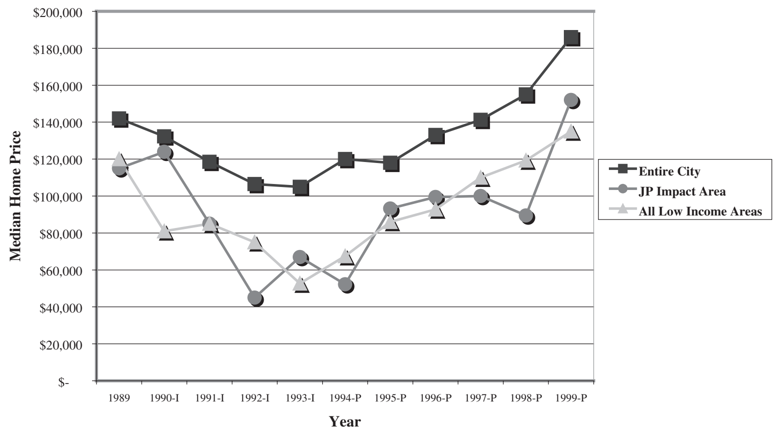

Figure 10: Property Value Changes in the Jamaica Plain Impact Area, Boston Low-Income Neighborhoods, and the City of Boston

NOTE: An "I" appended to any year denotes the interim intervention period, and a "P" denotes the postintervention period.

ble neighborhoods, before reversing themselves during the last half of the interim period. Thereafter, median home prices in the development area generally appeared to outpace growth in other low-income Boston neighborhoods, such that by 1999, they exceeded them by more than $10,000.

The AITS analysis paints quite a different portrait, however (see the appendix and Figure 11). The model's estimated parameters (negative for DIMP and positive for TRIMP) show that the impact area started 1988 with home prices roughly 69% lower than comparison neighborhoods but had eliminated the gap by 1990. However, the large negative coefficient for TRINTIMP offset the positive TRIMP coefficient, indicating that the Jamaica Plain impact area housing prices depreciated relatively during the interim period, eventually lagging 44% below the rest of the comparable Boston low-income market. On completion of the intervention in 1994, prices in the impact area began to climb slowly relative to other low-income areas (i.e., a positive coefficient of TRPOSTIMP created a net positive coefficient for the impact area across all periods), but the underperformance created during the interim period persisted by the end of 1999. Thus, the overall impact of the Jamaica Plain intervention as estimated by AITS appears to have been negative during our period of analysis. Compared with its relative trajectory prior to intervention, the net result of the Jamaica Plain community development plan appears to have been a reduction in the price level of homes in the impact area relative to other low-income Boston neighborhoods. This

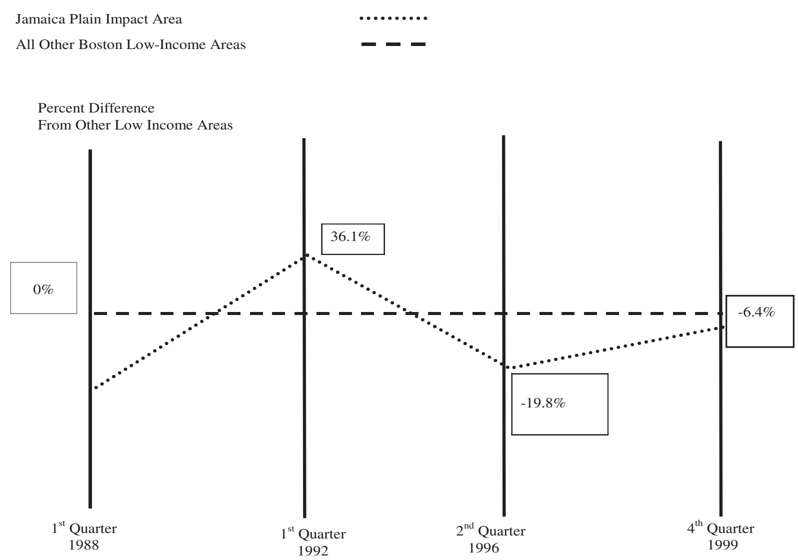

Figure 11: Econometric Trend Analysis of Property Value Change in Jamaica Plain Impact Area Compared With All Other Boston Low-Income Areas

NOTE: Lines indicate property value changes relative to other low-income areas in Boston after controlling for attributes of properties sold and general economic conditions.

result flies in the face of common sense, expert local opinion, and a cursory view of unadjusted home price trends. We believe that this statistical result was produced spuriously as a consequence of several potential weaknesses in the AITS approach that were manifested in this particular instance. It is to this critical discussion of the vulnerabilities of this approach that we now turn.

POTENTIAL SHORTCOMINGS OF THE AITS METHOD

Although we persist in our claim that the AITS method for evaluating the impacts of community development initiatives offers numerous advantages over extant approaches, we would be remiss in not discussing its unique potential shortcomings. Two are key. For a reliable estimation of the counterfactual scenario, AITS demands (a) substantial numbers of frequently recurring observations in the impact area before and after an intervention and (b) a well-behaved trend in the indicator before an intervention (Shadish, Cook, and Campbell 2002).

Given that the AITS approach uses the level and slope in the outcome indicator before an intervention as the basis for estimating the counterfactual scenario after an intervention, the precision of these preintervention parameter estimates is crucial. Two observations are mathematically sufficient, but more clearly would improve one's confidence in the estimates. In the case of single-family home sale prices, one requires a larger sample over a longer period to confidently distill secular trends from a distinct seasonality cycle. In certain types of neighborhoods—those with low rates of property turnover or high rates of multifamily rental housing—the use of AITS with home sale prices is risky or even infeasible.

But even with sufficient numbers of observations of the outcome indicator before and after an intervention, the AITS method may flounder if the indicator (especially during the preintervention period) is volatile. The AITS fits distinct linear functions to the pre- and postintervention scatters of observations. If the underlying relationships are more curvilinear or cyclical, however, these linear fits will be both imprecise and arbitrary, depending on the period over which observations are collected.[16]

Our application of the AITS approach to the Jamaica Plain initiative illustrates the consequences when both of the foregoing shortcomings are manifested. First, the preintervention period in the impact area was characterized by an unusual curvilinear pattern of home prices (see Figure 10). This high volatility, moreover, persisted throughout the postintervention period. Second, the impact area evinced the lowest rate of single-family home sales of any of our study sites, likely because of the preponderance of multifamily housing in the vicinity. Both factors conspired to render the AITS approach's projection of home prices into the interim and postintervention periods quite imprecise. As such, we place little confidence in the implication of a negative impact from the Jamaica Plain initiative.

Further, the method benefits from more rather than less housing price data on the pre- and postintervention periods. Again in Boston, the relatively short period, the paucity of single-family home sales, and the peculiar price behavior in the preintervention period rendered the model's performance suspect; a more extended preintervention period might have allowed us to correct for this. Finally, the model relies on information on single-family residential transactions, which may display trends that would be different from those in multifamily residential or commercial markets, especially where the impact area is dominated by these kinds of properties.

SUMMARY AND CONCLUSION

We have attempted in this article to contribute to the development of empirical methods for measuring the impacts of place-based local development strategies. Previous approaches have typically foundered against the challenge of estimating the counterfactual scenario of how the outcome indicator of interest would have performed in the impact neighborhood in the absence of the intervention. We introduced a method, the AITS approach, that advances the precision of this counterfactual situation and offers a stronger basis for drawing causal inferences. In particular, it avoids the neighborhood selection bias by using the preintervention level and slope of the indicator in the impact neighborhood as the basis for estimating the counterfactual scenario in the postintervention period, after adjustment by any changes in the trends in control neighborhoods.

We applied the AITS approach in three case studies of large-scale, CDC-led community development initiatives in Portland, Denver, and Boston, using single-family home prices as the outcome indicator. We found the method capable of measuring impacts that manifested themselves as a change in either the base level of prices or the rate of price appreciation, an important distinction that prior approaches have blurred. We also found in the case of Boston, however, a situation in which the method appears unreliable. The AITS method benefits from more recurrent data on outcomes during the pre- and postintervention periods and an intertemporal pattern in such data (especially during the preintervention period) that avoids great volatility. In the case of Boston, the paucity of single-family home sales in the impact neighborhood and peculiar price behavior in the preintervention period badly eroded the model's performance. Of course, the veracity of all previous approaches will be weakened in cases of limited and/or highly volatile data, so this criticism is hardly unique to the AITS approach.

In conclusion, the AITS approach to measuring effects of community development initiatives holds strong promise, on the basis of our theoretical critique of alternative methods and our prototype experiments. Of course, the method is feasible only when there are frequently recurrent observations of the indicator both before and after an intervention. Moreover, in contexts of thin, volatile data, the method has clear limitations. Nevertheless, we believe it warrants additional experimentation in a wide range of programmatic applications.

APPENDIX

Estimated Coefficients (*SE*s) for Impact Variables in Adjusted Interrupted Time-Series Analyses (Dependent Variable: Natural Log of Home Sale Price)

	Portland			Denver			Boston		
Variable	*Coefficient*	SE	t *Statistic*	*Coefficient*	SE	t *Statistic*	*Coefficient*	SE	t *Statistic*
Price level variables									
DIMP impact area: all periods[a]	–0.088	0.086	–1.026	–0.221	0.115	–1.918	–1.369	0.652	–2.098
DINTIMP impact area: interim and postintervention periods	0.311	0.127	2.444	0.086	0.187	0.461	–0.070	0.161	–0.434
DPOSTIMP impact area: postintervention period	0.526	0.224	2.346	0.086	0.273	0.317	0.149	0.289	0.515
Price trend variables									
TRIMP impact area: all periods[a]	–0.007	0.005	–1.198	–0.032	0.027	–1.207	0.202	0.094	2.145
TRINTIMP impact area: interim and postintervention periods	–0.003	0.019	–0.139	–0.005	0.036	–0.126	–0.241	0.095	–2.538
TRPOSTIMP impact area: postintervention period	–0.029	0.045	–0.655	0.043	0.024	1.770	0.047	0.016	2.964
Sample *N*		104,505			64,682			33,349	

NOTE: All regressions use a constant and control variables for home characteristics, quarter-year, census tract, and spatial heterogeneity; White's (1980) standard errors are reported.
a. Compared to all other low-income neighborhoods in that city.

NOTES

1. Shadish, Cook, and Campbell refer to AITS as “interrupted time series with nonequivalent, no treatment control group time series” (p. 182).

2. In this article, we do not address the use of qualitative methods to assess impacts; see Sullivan (1990).

3. For a comprehensive treatment of this subject with an exhaustive set of illustrative studies, see Hollister and Hill (1995). See Shadish, Cook, and Campbell (2002) for a discussion of quasi-experimental design techniques and illustrations from a range of fields.

4. This approach is fundamentally consonant with a shift-share analysis (Dowall, Beyeler and Wong, 1994).

5. This observation was first made by Schill et al. (2002).

6. We recognize that there is nearly always some combination of ambient level of community development activities going on in nearly every low-income neighborhood. The value of the AITS method is that one does not need to worry about that, as long as one is willing to assume that in no other neighborhoods are there significant interventions occurring with exactly the same timing such that they would confound the average over all low-income neighborhoods. One can test this assumption by interviewing local informants. Of course, any impact evaluation design is vulnerable to idiosyncratic local events impinging on either intervention or control neighborhoods.

7. Note that our approach is different from that of Schill et al. (2002), which uses a fixed-effects model that has separate dummy variables for each time period within a census tract to control for neighborhood conditions in pre- and postintervention time periods. We believe that our specification, by allowing for a measured change in both the level and the trend in an intervention area, provides for more substantive results. Namely, our specification provides program evaluators with evidence that a targeted intervention resulted in either a onetime change in neighborhood conditions, which would be manifested by a statistically significant change to the DPOSTIMP variable, or a change in the rate of change (TRPOSTIMP), or both.

8. Note that because of the irregularity of sales across time and space and the lack of any standard spatial unit of analysis, it is not appropriate to treat this model as a straightforward panel.

9. Details about the data and model can be obtained from the first author.

10. This model represents a variant of a model that was originally developed to test the neighborhood home price externality impacts of a multiple number of small-scale, subsidized housing developments (see Galster, Tatian, and Smith 1999; Galster et al. 2000). Subsequently, the basic approach was enhanced in several valuable ways by Johnson and Bednarz (2002); Ellen et al. (2001); Schill et al. (2002); and Schwartz, Ellen, and Voicu (2002).

11. These interim periods typically lasted a few years; details are provided below.

12. We also investigated impacts in a secondary impact area defined by a ring of blocks within a quarter mile of the primary impact area. Results for these areas were generally less statistically and economically significant, and their inclusion does not alter or enhance the basic conclusions of our analysis.

13. Shadish, Cook, and Campbell (2002:201-2) recommend such visual inspection, though not as the exclusive means of analysis.

14. In a log-linear model, the coefficient c cannot be directly interpreted as the percentage change in the dependent variable associated with the dummy changing from 0 to 1. Rather, the relative impact is given by $\exp(c) - 1$ (Halvorsen and Palmquist 1980). Here, the full effect for the

postintervention period is found by summing the coefficients for DINTIMP and DPOSTIMP for Area 1 and applying the above formula.

15. See the coefficient of DIMP for Area 1 in the appendix.

16. In principle, one might imagine specifying nonlinear modifications of equation 1, but such is beyond the scope of the current article.

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