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Teardowns and land values in the Chicago metropolitan area ☆

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Abstract

An empirical model of residential housing demolitions and the redevelopment process in the Chicago metropolitan area supports the theoretical prediction that the sales price of teardown property is approximately equal to its land value. We control for sample selection bias associated with non-random demolition permit applications using a probit model that accounts for misclassification of the dependent variable. The probit models provide statistically significant evidence of misclassification, and suggest that prime teardown candidates are small, older, homes near public transportation and traditional village centers.

Keywords: Redevelopment; Demolition; Teardowns; Misclassification; Housing prices; Land values; Hedonic models

1. Introduction

For years American cities grew by building homes at the urban fringe. A common explanation is that underlying economic factors such as higher incomes and lower commuting costs tend to push people away from the traditional city center. The tendency toward decentralization is accentuated when good schools, low crime rates, and rapid job growth are concentrated in suburban areas. A burgeoning literature on "urban sprawl" suggests that the decentralization process remains unabated (for an overview see Nechyba and Walsh [16]).

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At the same time that new housing is being built on the fringe, there is also a process of "redevelopment," wherein existing housing in established locations is being torn down and replaced by new housing. In some places this is part of the process of "gentrification," with high-income households moving back toward the central city and inner-ring suburbs replacing long-time residents with lower incomes.[1] In other places, residences in neighborhoods already occupied by high-income households are simply being replaced by newer, more expensive, and often much larger homes. Extensive renovation and remodeling is another common way of upgrading the existing housing stock.

Redevelopment has benefits in that it typically adds to a city's tax base by replacing old buildings with high-priced homes, and it may deter urban sprawl by allowing people who prefer new homes to build nearer the city center. However, it also has costs, in that increasing home prices and taxes may force some existing residents to move elsewhere. By creating noise and interfering with local traffic patterns, new construction is often disruptive, particularly in built-up areas. Existing residents complain that new homes are so large and of such contrasting styles that they overwhelm older buildings and destroy a neighborhood's character.

Chicago is one of the metropolitan areas where redevelopment is widespread. McMillen [14] documents the return of a significant house-price gradient in Chicago, and Sander [18,19] shows that the impact of education on demand for central city living interacts with race. Expensive homes that sometimes push the limits of local building regulations are being built in both the city and suburbs. When new buildings replace existing structures, the often controversial practice is referred to as "teardowns," "knockdowns," or "scrape-offs" in different locales. Several suburbs have recently modified their building codes or enacted other ordinances to discourage teardowns. In an attempt to slow the rate of redevelopment and allow time to assess the "historic and/or architectural significance" of targeted structures, one Illinois suburb where teardowns are widespread has imposed a nine-month delay between the time a demolition permit is issued and the date when it can be acted upon (Village of Kenilworth [21]).

In this paper, we develop an empirical model of demolitions and the redevelopment process in the Chicago metropolitan area. We focus on Chicago neighborhoods and suburbs where teardowns are widespread. Our empirical approach builds on the seminal paper by Rosenthal and Helsley [17], who analyze redevelopments in Vancouver, British Columbia. We use a probit model to estimate the probability that a demolition permit has been issued for a home. We then estimate hedonic price functions for both the homes with demolition permits and the control sample. The estimation procedure controls for the sample selection bias associated with non-random demolition permit applications.

Our approach differs from Rosenthal and Helsley [17] and subsequent studies by Munneke [15] and McGrath [13] in two important ways. First, we control for misclassification using a procedure proposed by Hausman, Arbrevaya, and Scott-Morton [8]. Throughout the paper we use the term "teardown" to represent "redevelopment"—the demolition and replacement of a residential structure. We use demolition permits as a proxy for redevelopment. The proxy introduces several possible sources of misclassification. First, the permit may be issued, but the house may not end up being torn down. Second, the house may be demolished, but the lot may be left vacant or converted to a non-residential use. Third, the house may be renovated to the point of being

[1] Helms [10] and Vigdor [20] are examples of studies of gentrification. The study by Brueckner and Rosenthal [2] extends the traditional monocentric city model to an explicitly dynamic setting in which houses age and high-income households must decide between moving to the urban fringe or redeveloping inner-ring areas to satisfy their demand for new, high-quality housing.

virtually new without ever receiving a demolition permit. Thus, some of the observations that have received permits are actually not teardowns while other observations without permits are comparable to the sample of teardowns. Our results imply statistically significant degrees of misclassification, and controlling for misclassification improves the fit of the second-stage hedonic price functions.

The second way in which our study differs from previous work is that our data set includes the housing characteristics for the sample of homes that have been torn down. This additional set of variables allows us to test a critical prediction of the theory—that when a home is sold prior to being torn down, its sales price reflects only the value of the land, rather than the characteristics of the home itself. This prediction is borne out in our empirical models.

The results provide insights into the redevelopment process. We find that older homes that have low floor-to-land-area ratios are more likely to be torn down than others. Homes with amenities such as brick construction and basements are less likely to be demolished, particularly in the city where these amenities are less common in existing homes. Thus, the selection process is far from random: demolition permits are more likely to be issued for inexpensive, older homes in the midst of a high-demand area. Although these housing characteristics alter the probability that a home will be demolished, they do not affect its sales price at the time prior to its being torn down. This result provides strong support for Rosenthal and Helsley's suggestion that teardown prices provide a good approximation to the value of land in built-up urban areas.

2. A hedonic model of house prices, land values, and teardowns

Teardowns are not drawn randomly from the population. Developers often look for older, smaller homes on large lots to replace with new houses built to the limits of local building codes and zoning regulations. Well-maintained, high-priced houses are less likely to be demolished than homes whose poor condition has led to relatively low sales prices. Thus, factors determining sales prices also influence the probability that a home is demolished. Not all of these determinants of sales prices and teardown status are readily observable or measurable. Hedonic price function estimates will be subject to selection bias because the errors of the sales price and teardown status equations are likely to be correlated.

Rosenthal and Helsley [17] used a standard Heckman [9] two-stage procedure to control for selection bias in the estimated hedonic house price equation. Our exposition starts with this standard approach and then extends it. Let y_1 represent the natural logarithm of the sales price of a home as a teardown, while y_0 is the log sales price of a non-teardown sale. The hedonic price functions for the two types of sales are given by the following equations:

$$y_0 = X\beta_0 + u_0, \tag{1}$$

$$y_1 = X\beta_1 + u_1. \tag{2}$$

Teardown status, which is a function of a set of explanatory variables Z, is indicated by the discrete variable $\tilde{T}$, with $\tilde{T} = 1$ if the home is sold as a teardown and $\tilde{T} = 0$ otherwise. With the addition of an error term that is assumed to be normally distributed, the teardown status equation is given by

$$\tilde{T} = 1 \quad \text{if } Z\lambda + v \geqslant 0, \tag{3a}$$

$$\tilde{T} = 0 \quad \text{if } Z\lambda + v < 0. \tag{3b}$$

The sales price y_o is observed if $\tilde{T} = 0$ and y_1 is observed if $\tilde{T} = 1$. Estimating equations for the Heckman procedure are based on the conditional expectations:

$$E(y_{0i} \mid \tilde{T}_i = 0) = X_i\beta_0 - \sigma_{0v}\frac{\phi(Z_i\lambda)}{1-\Phi(Z_i\lambda)}, \tag{4}$$

$$E(y_{1i} \mid \tilde{T}_i = 1) = X_i\beta_1 + \sigma_{1v}\frac{\phi(Z_i\lambda)}{\Phi(Z_i\lambda)}. \tag{5}$$

The usual procedure is to estimate these equations separately for the observations where $\tilde{T} = 0$ and $\tilde{T} = 1$. Although the approach is less common, it is also possible to combine the two sets of observations into a single estimating equation using the relationship $E(y_i \mid \tilde{T}_i) = (1-\tilde{T}_i)E(y_{0i} \mid \tilde{T}_i = 0) + \tilde{T}_i E(y_{1i} \mid \tilde{T}_i = 1)$. The result is

$$E(y_i \mid \tilde{T}_i) = (1-\tilde{T}_i)X_i\beta_0 + \tilde{T}_i X_i\beta_1 - \sigma_{0v}(1-\tilde{T}_i)\frac{\phi(Z_i\lambda)}{1-\Phi(Z_i\lambda)} + \sigma_{1v}\tilde{T}_i\frac{\phi(Z_i\lambda)}{\Phi(Z_i\lambda)}. \tag{6}$$

A variant of Eq. (6) will form the basis of our estimating equation when the probit model is subject to misclassification.

The theory presented in Rosenthal and Helsley [17] predicts that a teardown occurs when property value has depreciated to the point where the sales price equals its value as vacant land less any demolition cost. Under the reasonable expectation that demolition costs are low,[2] teardown sales prices are a good approximation for land values. This insight is important for assessment purposes because it is often difficult to estimate land values in built-up urban areas where sales of vacant land are uncommon. Teardown sales may provide an alternative way to obtain accurate assessments of land values if the theoretical predictions are supported by the data. By definition, land values reflect the value of location rather than characteristics of the structure built on the site. Thus, the crucial theoretical prediction is that only characteristics of the location affect the sales prices of teardowns, whereas both locational and structural characteristics affect non-teardown sales prices. If we decompose the vector of house price determinants into characteristics of the structure (S) and the location (L), so that $X\beta = S\theta + L\delta$, then we should find that $\theta = 0$ in the teardown house price equation. Unfortunately, Rosenthal and Helsley [17] were not able to test this prediction because their data set did not include any structural characteristics other than the age of the building.

Teardown status is not always readily observable and demolition permits are an imperfect proxy for redevelopment. Demolition does not necessarily follow the issuing of a permit and rebuilding does not necessarily follow demolition. Building permits are issued separately from demolition permits, and the lists of the two types of permits can prove difficult both to obtain and to merge. Moreover, some homes are remodeled so extensively that they are effectively teardowns even if they are not literally demolished. As is the case with a true teardown, if a home is sold prior to a major renovation, structural characteristics are likely to have less influence on the sales price than when the home is not renovated subsequent to the sale. In the extreme case, homes are so extensively remodeled that they are effectively new, and the sale prior to renovation little different from a teardown sale. Thus, the dependent variable for the teardown probability equation may suffer from misclassification: some observations that are classified as teardowns may not have been demolished and replaced, while observations that are classified as non-teardowns may actually be equivalent to teardown sales.

Hausman, Abrevaya, and Scott-Morton [8] develop a simple estimation procedure that controls for misclassification of the dependent variable in a probit model. Let T represent observed

[2] For part of our sample we have demolition cost estimates reported on the permits. For structures with three or fewer units and that report a non-zero value, the median demolition cost is $7100.

teardown status, while $\tilde{T}$ continues to represent the actual status. The probability that a non-teardown is classified as a teardown is given by α_0, while the probability that a teardown is recorded as a non-teardown is given by α_1. These probabilities, which are assumed to be independent of Z, are defined formally as follows:

$$\alpha_0 = \Pr\bigl(T = 1 \bigm| \tilde{T} = 0\bigr), \tag{7a}$$

$$\alpha_1 = \Pr\bigl(T = 0 \bigm| \tilde{T} = 1\bigr). \tag{7b}$$

Assuming the errors are normally distributed, the probability that an observation is actually a teardown is $\Pr(\tilde{T} = 1 \mid Z) = \Phi(Z\lambda)$, while the probability that it is a non-teardown is $\Pr(\tilde{T} = 0 \mid Z) = 1 - \Phi(Z\lambda)$. In fact, there is an α_0 probability that a non-teardown observation has been incorrectly classified as a teardown, while there is a $1 - \alpha_1$ probability that a teardown observation has been correctly classified as such. Thus, the probability that an observation has been classified as a teardown is

$$\Pr(T = 1 \mid Z) = (1 - \alpha_1)\Phi(Z\lambda) + \alpha_0\bigl(1 - \Phi(Z\lambda)\bigr) = \alpha_0 + (1 - \alpha_0 - \alpha_1)\Phi(Z\lambda). \tag{8}$$

Similarly, the probability that an observation is classified as a non-teardown is

$$\Pr(T = 0 \mid Z) = \alpha_1\Phi(Z\lambda) + (1 - \alpha_0)\bigl(1 - \Phi(Z\lambda)\bigr) = 1 - \alpha_0 - (1 - \alpha_0 - \alpha_1)\Phi(Z\lambda). \tag{9}$$

The log-likelihood function for the probit model with misclassification is given by

$$\begin{aligned}\ln L &= \sum_{i=1}^{n}\bigl\{T_i \ln\bigl(\Pr(T_i = 1 \mid Z_i)\bigr) + (1 - T_i)\ln\bigl(\Pr(T_i = 0 \mid Z_i)\bigr)\bigr\} \\ &= \sum_{i=1}^{n}\bigl\{T_i \ln\bigl(\alpha_0 + (1 - \alpha_0 - \alpha_1)\Phi(Z\lambda)\bigr) + (1 - T_i)\ln\bigl(1 - \alpha_0 - (1 - \alpha_0 - \alpha_1)\Phi(Z\lambda)\bigr)\bigr\}.\end{aligned} \tag{10}$$

If the model's assumptions are correct, maximizing Eq. (10) with respect to α_0, α_1, and λ provides consistent and efficient estimates of λ as well as the probabilities of misclassification. This approach has been used in studies by Bollinger and David [1], Caudill and Mixon [3], Dustman and Van Soest [4,5], Fay, Hurst, and White [6], Frazis and Loewenstein [7], Kenkel, Lillard, and Mathios [11], and Leece [12].

The misclassification does not affect the conditional expectations for the hedonic price functions, which are based on actual teardown status. However, basing the estimates on observed

Table 1
Expected prices and probabilities with misclassification of teardown status

Actual teardown status	Observed teardown status: $T = 0$ Non-Teardown	Observed teardown status: $T = 1$ Teardown
$\tilde{T} = 0$ Non-Teardown	$E\bigl(y \mid \tilde{T} = 0\bigr) = X\beta_0 - \sigma_{0v}\frac{\phi(Z\lambda)}{1-\Phi(Z\lambda)}$ $Prob = (1 - \alpha_0)\bigl(1 - \Phi(Z\lambda)\bigr) = P_{00}$	$E\bigl(y \mid \tilde{T} = 0\bigr) = X\beta_0 - \sigma_{0v}\frac{\phi(Z\lambda)}{1-\Phi(Z\lambda)}$ $Prob = \alpha_0\bigl(1 - \Phi(Z\lambda)\bigr) = P_{01}$
$\tilde{T} = 1$ Teardown	$E\bigl(y \mid \tilde{T} = 1\bigr) = X\beta_1 + \sigma_{1v}\frac{\phi(Z\lambda)}{\Phi(Z\lambda)}$ $Prob = \alpha_1\Phi(Z\lambda) = P_{10}$	$E\bigl(y \mid \tilde{T} = 1\bigr) = X\beta_1 + \sigma_{1v}\frac{\phi(Z\lambda)}{\Phi(Z\lambda)}$ $Prob = (1 - \alpha_1)\Phi(Z\lambda) = P_{11}$
Column sum	$P_0 \equiv (1 - \alpha_0) - (1 - \alpha_0 - \alpha_1)\Phi$	$P_1 \equiv \alpha_0 + (1 - \alpha_0 - \alpha_1)\Phi$

teardown status leads to biased results if some observations are misclassified. Table 1 shows the combination of expected prices and probabilities. As in the model with no misclassification, the first row shows that the probability of a non-teardown is $(1-\Phi(Z_i\lambda))$ and that the expected price conditional on non-teardown status is as before. Similarly, the second row shows the probability of a teardown, $\Phi(Z_i\lambda)$, and the expected price conditional on teardown status. Misclassification serves to break the link between actual and observed teardown status. Focusing on the second row of equations in Table 1, the probability that an observation is correctly observed to be a teardown is the product of the probability that it is actually a teardown and the probability that it is not misclassified, or $(1-\alpha_1)\Phi(Z_i\lambda)$. Similarly, the probability that a teardown is misclassified as a non-teardown is the probability that it is actually a teardown and the misclassification probability, or $\alpha_1\Phi(Z_i\lambda)$. The calculations in the first row are similar for observations that are actually non-teardowns.

The conditional expectations based on observed teardown status, $E(y \mid T=0)$ and $E(y \mid T=1)$, combine teardown observations with non-teardowns. Using the results from Table 1, the expectation of y given that the observation is observed to be a non-teardown is $E(y \mid T=0) = \Pr(\tilde{T}=0 \mid T=0)E(y \mid \tilde{T}=0) + \Pr(\tilde{T}=1 \mid T=0)E(y \mid \tilde{T}=1)$. Similarly, the expectation of y given that the observation is observed to be a teardown is $E(y \mid T=1) = \Pr(\tilde{T}=0 \mid T=1)E(y \mid \tilde{T}=0) + \Pr(\tilde{T}=1 \mid T=1)E(y \mid \tilde{T}=1)$. Gathering the terms for the conditional expectations for y, we have

$$\begin{aligned} E(Y \mid T) = {} & \bigl\{(1-T)\Pr\bigl(\tilde{T}=0 \mid T=0\bigr) + T\Pr\bigl(\tilde{T}=0 \mid T=1\bigr)\bigr\}E\bigl(Y \bigm| \tilde{T}=0\bigr) \\ & + \bigl\{(1-T)\Pr\bigl(\tilde{T}=1 \mid T=0\bigr) + T\Pr\bigl(\tilde{T}=1 \mid T=1\bigr)\bigr\}E\bigl(Y \bigm| \tilde{T}=1\bigr). \end{aligned} \tag{11}$$

From Table 1, the probabilities are $\Pr(\tilde{T}=a \mid T=b) = P_{ab}/P_b$. Thus,

$$E(Y \mid T) = \left\{(1-T)\frac{P_{00}}{P_0} + T\frac{P_{01}}{P_1}\right\}E\bigl(Y \bigm| \tilde{T}=0\bigr) + \left\{(1-T)\frac{P_{10}}{P_0} + T\frac{P_{11}}{P_1}\right\}E\bigl(Y \bigm| \tilde{T}=1\bigr). \tag{12}$$

Define $\psi = (1-T)P_{10}/P_0 + T\,P_{11}/P_1$ and note that the first term in brackets in Eq. (12) is equal to 1-ψ. The counterpart to Eq. (6) is

$$E\bigl(y_i \mid T_i\bigr) = (1-\psi_i)X_i\beta_0 + \psi_i X_i\beta_1 - \sigma_{0v}(1-\psi_i)\frac{\phi(Z_i\lambda)}{1-\Phi(Z_i\lambda)} + \sigma_{1v}\psi_i\frac{\phi(Z_i\lambda)}{\Phi(Z_i\lambda)}. \tag{13}$$

This equation simplifies to Eq. (6) if $\alpha_0 = \alpha_1 = 0$. When some observations are misclassified for the probit model, Eq. (13) shows that the conditional expectation is a weighted average of the expected value as a teardown and as a non-teardown, where the weights depend on ψ_i.

3. Teardowns in the Chicago metropolitan area

Our analysis focuses on seven communities where we were able to obtain detailed data on demolition permits. However, the teardown phenomenon is important in other Chicago area communities (Village of Skokie [22]) and in communities across the nation.[3] A rough measure of the extent of residential housing teardowns in an area, what we call the "net replacement rate," can

[3] Web searches for "teardowns," "scrape-offs," or "knockdowns" produce numerous references from the journalistic literature or local government reports across the country.

be obtained from decennial Census of Housing data: the approximate number of demolish-and-replace units is equal to the number reported in 2000 as being built since 1990 minus the change in the total number of housing units between 1990 and 2000. The measure is only an approximation, because an area that is not fully built-up could have demolitions in one location and replacement housing built on vacant or converted land in another. We calculate this measure, expressed as a percent of the number of housing units in 1990, for Census tract data. Selection criteria, chosen to make the net replacement rate statistic better approximate teardown and replacement on the same site, restrict the sample to 7667 Census tracts.[4] The resulting distribution of net replacement rates as a fraction of the housing stock has: one-tenth of the tracts over 5.2 percent; one-twentieth of the tracts over 7.1 percent; and one percent of the tracts over 12.3 percent. The Census tracts with high net replacement rates are clustered in older urban areas in the Northeast, Midwest, and California. Replacement of the preexisting housing stock is an extensive phenomenon that is national in scope.

The City of Chicago provided a file listing the building and demolition permits issued in Chicago between 1993 and 2004 (for a description of this data set and its use in a logit model of the demolition decision, see Weber et al. [23]). We also obtained demolition permit data directly from six suburban communities with active teardown markets—Glencoe, Kenilworth, Park Ridge, Western Springs, Wilmette, and Winnetka. We were able to obtain permit data for 1996–2003 for Glencoe, Kenilworth, Wilmette, and Winnetka. Permit data were only available for 2000–2003 for Park Ridge and for 1999–2003 for Western Springs. We used the parcel identification number to merge the demolition permits with the assessment rolls for the full county for 1997 and 2003. The assessment file lists the property's address along with such standard structural characteristics as lot size, building area, age, garage size, and the presence of a basement, fireplace, brick construction, and central air conditioning. We use the demolition permits to identify potential teardowns. Our assessment data are limited to residential properties with six units or fewer in Chicago and single family units in the suburbs.

Table 2 shows the number of demolition permits issued by year in these communities. Whereas the number of permits has risen fairly steadily over time in the suburbs, the demolition activity peaked in Chicago in the late 1990s. Chicago is so large that its numbers dwarf those of its suburbs. To put the teardown numbers in perspective, Table 2 also shows the number of teardowns in each community as a percentage of its total housing stock in 2003. By this measure, the most active teardown markets were Glencoe, Western Springs, and Winnetka. Over the entire 1996–2003 period, Glencoe had 230 teardowns, representing 7.93% of its housing stock. Western Springs had 182 teardowns (4.32%) and Winnetka had 373 teardowns (9.40%). Chicago had 12,236 demolition permits issued, representing 2.90% of its 2003 housing stock.[5]

The suburban sample municipalities are wealthier than the average of all Chicago-area suburbs. Glencoe, Kenilworth, Wilmette, and Winnetka are on the North Shore—the wealthy strip of land along Lake Michigan to the north of Chicago. Western Springs is a comparable community in the western suburbs. Park Ridge is a moderately high-income suburb on the near northwest side. All six suburbs are completely built, and most have an ample stock of smaller, 1950s-vintage homes that are ripe for redevelopment.

[4] The selection criteria are: no change in land area, median year-built of housing stock 1970 or earlier, population 1000 or greater, number of housing units 100 or greater, overall growth in the number of units is between negative one half percent and positive ten percent.

[5] Indeed, the actual percentages are higher since our measure has *structures* demolished in the numerator and the Census counts of housing *units* in the denominator and there are fewer total structures than units.

Table 2
Demolition permits by year

	Chicago	Glencoe	Kenilworth	Park Ridge	Western Springs	Wilmette	Winnetka
1993	1191						
1994	1244						
1995	1386						
1996	2002	8	1			13	40
1997	1595	19	4			16	44
1998	1712	30	3			36	44
1999	1654	43	3		27	34	48
2000	1617	31	3	54	39	35	55
2001	1325	30	4	64	34	39	58
2002	1224	27	3	51	37	34	35
2003	1107	42	8	82	45	52	49
Total, 1996–2003	12,236	230	29	251	182	259	373
Total as % of housing stock	2.90	7.93	3.52	2.11	4.32	3.08	9.40
Population	2,896,016	8762	2494	37,775	12,493	27,651	12,419
Median income	38,625	164,432	200,000+	73,154	98,876	106,773	167,458
Median home value	132,400	667,000	972,000	295,800	323,900	441,600	756,500

Notes. All data other than demolition permits are drawn from the 2000 Census. A blank indicates that no data is available for that year. Total demolition permits as a percentage of housing stock are calculated using 2000–2003 permits in Park Ridge and 1999–2003 permits in Western Springs.

Demolition permits are not necessarily synonymous with redevelopment. Some permits that are issued are never used—an issue that we address explicitly in our estimation procedure. Moreover, demolition may not be followed by new construction if the objective is simply to clear a dilapidated structure. Rapid redevelopment is virtually certain in the suburban communities and in high-priced areas of the city with rapid appreciation rates. Chicago is so large and diverse that it is difficult to model adequately with a single set of equations. To assure a reasonably homogeneous sample that can be represented accurately with a single empirical model, we restrict our analysis to Chicago's north-side community areas of Lakeview, Lincoln Park, Logan Square, North Center, and West Town. As in the suburban communities, demolition permits are very likely to be followed by redevelopment in these five community areas. As noted earlier, data limitations preclude us from identifying redeveloped properties precisely.

4. Additional data

The Cook County Assessor's Office provided data for the 1997 and 2003 assessment years that included standard housing characteristics. After geocoding the properties, we added several important locational characteristics. We calculate distance to Lake Michigan, which is an important amenity in the Chicago area. The rail lines that riddle the entire Chicago area create noise and the non-residential uses that locate along the lines may lower nearby residential property values. To control for these disamenities, we create a dummy variable indicating that a property is within one block (an eighth of a mile) of a rail line. For all properties, we measure distance to the nearest highway interchange. For Chicago properties, we calculate distance to the nearest stop on the rapid transit line (the "El"). For suburban properties, we construct a comparable variable measuring distance to the nearest stop on a commuter train line. All distances are measured in straight-line miles.

The Illinois Department of Revenue (IDOR) provided data on home sales. The IDOR obtains data from property transfer declarations to conduct assessment ratio studies. The dataset includes little information other than prices and sales dates. Importantly, it includes the parcel identification number, which allows us to merge the sales data with the data from the Assessor's Office. Data are available on sales up to 2002.

The timing of the sale is a critical issue in merging the IDOR sales data with the teardown permit data. To estimate land value, we want to identify properties that have been purchased with the intention of demolishing the structure in the near future. For this reason, we do not include sales that have taken place during or after the calendar year of the application for a demolition permit. Instead, we restrict our sample to sales that took place in the two years prior to the calendar year of the demolition permit application. It seems likely that sales during the two prior years will reflect the intent to eventually demolish the property. Experiments with other sample cutoffs—including sales from the year of the permit, restricting sales to just the year preceding the permit, or including three years prior to the permit—lead to qualitatively similar results.

We restrict our sample to two sets of properties:

(1) those that never have a demolition permit but which sold between 1995 and 2002, and
(2) those with a permit issued between 1997 and 2003.

For the Chicago sample, we exclude any properties with demolition permits issued before 1997 because we cannot observe their housing characteristics prior to this date. We use all properties with demolition permits issued during 1997–2003 to estimate our probit model of teardown probabilities. To estimate the hedonic sales price models for teardown properties, we use the subset of homes with both permits and sales during the two years prior to the permit application. Thus, the sample of sales prices covers 1995–2002 for both teardown and non-teardown sales.

Explanatory variables for the probit models of teardown probabilities include

(1) characteristics of the location,
(2) housing characteristics as of 1997,
(3) various neighborhood indicators, and
(4) the age, land area, and building area of the existing home relative to the census tract average.

For Chicago, our neighborhood indicators for the probit models are the community area and the Aldermanic ward in which the property is located. Community areas are Chicago's traditional definition of neighborhoods. In addition, Chicago has 50 wards, each of which has an elected alderman. Aldermen frequently have effective veto power over building permits, and some are much more sympathetic to new construction than others. Thus, this variable is an important addition to the list of explanatory variables for the probit model. For the suburban data, we include dummy variables for the municipality. The comparison group is the complete set of homes listed in the Assessor's data file that do not have any missing housing characteristics data for 1997. For Chicago, we include a dummy variable indicating that the structure is a multi-family (2–6 unit) building. In the suburban communities, we restrict the analysis to single-family homes because multi-family teardowns are rare.

The final set of variables in the probit model includes the age, land area, and building area relative to the census tract average. The point of these variables is to control for the difference between a home and other buildings in the neighborhood. Developers claim to be selective in the buildings they choose for demolitions, seeking older, smaller homes in high-demand areas. These variables are particularly useful because they provide a means of obtaining identification beyond the nonlinearity of the probit model. Whereas at least one variable must be omitted from each equation that is not in the other equation to identify all the coefficients in a traditional linear two-equation system, nearly any variable that affects the probability of having a demolition permit also affects sales prices.[6] If the final consumer cares about the actual size and age of the home rather than the relative values, then these variables can be expected to affect the probability that a home is purchased for redevelopment without directly influencing the final sales price.

For our hedonic sales price models, we include the same basic set of explanatory variables in the regressions. In addition, we include dummy variables indicating the year of sale. Following the most common practice, the natural logarithm of sales price is the dependent variable for our hedonic model. We expect land and building area to interact differently for buyers and producers of housing. Buyers presumably care directly about lot size and building area when bidding for a home. Thus, we follow common practice and use the natural logarithms of land and building area as separate explanatory variables in the sales price models. The attractiveness of a property as a teardown is also directly affected by building density—the ratio of building to land area—because zoning provisions directly regulate density in the Chicago area. In addition, it is more expensive to rebuild high density properties: tall buildings are costly to tear down, while large lots leave more room to operate when constructing a new building. Including density in the probit model while land and building areas enter the sales price equation assists in identification by providing independent variation across the two equations.

5. Probit models of teardown probabilities

The probit models of teardown probabilities are presented in Tables 3 and 4. The dependent variable for these models is a discrete variable that equals one when a demolition permit was issued between 1997 and 2003. The dependent variable equals zero for properties with no permits issued during the entire time covered by our permit database. The tables present both standard probit estimates and the results of the Hausman, Arbrevaya, and Scott-Morton [8] misclassification model, which are obtained by maximizing Eq. (10) with respect to λ, α_0, and α_1.

Table 3 presents the probit estimates for Chicago. Teardown probabilities are estimated to be higher nearer El stops and close to Lake Michigan. Higher building densities (floor space to land area ratios) decrease the probability of a demolition permit being issued, a result that is consistent with the common belief that smaller homes are being replaced with new houses that are more likely to be built at a higher density. Homes on relatively large lots are less likely to be demolished, as are homes that are older than the census tract average. Multi-family structures are also more likely to be demolished. These results are consistent with the trend toward replacing older multi-family homes with single-family residences. If the redevelopment trend favors single-family homes, then our result that buildings on smaller lots are more likely to be demolished is not surprising. Moreover, areas with small lots typically are in high demand. Other structural characteristics influencing teardown probabilities are indicators that a structure is built using

[6] Comparing Eqs. (6) and (13) reveals that the same identification conditions apply for the misclassification model and the standard Heckman model. Although the equations are identified by the nonlinearity of the probit model, most researchers prefer to obtain identification by excluding variables from the $E(y \mid T = 0)$ and $E(y \mid T = 1)$ that are included in the first-stage probit model.

Table 3
Probit models of teardown probabilities: Chicago

Variable	Standard probit		Misclassification model	
	Coef.	Std. Err.	Coef.	Std. Err.
Distance from nearest El Stop	−0.6999*	0.0962	−0.7794*	0.1229
Within 1/2 mile of Lake Michigan	0.2626**	0.1401	0.2790**	0.1628
Within one block of rail line	−0.0397	0.0425	−0.0457	0.0468
Log of land area	0.1691	0.1346	0.4916*	0.1687
Log of building density	−1.1175*	0.1192	−1.1714*	0.1694
Age in 1997	−0.0009	0.0020	−0.0008	0.0023
Land area relative to tract average	−0.0515*	0.0140	−0.0694*	0.0182
Building area relative to tract average	0.1106	0.1273	−0.0224	0.1656
Age relative to tract average	0.7233*	0.1576	0.8413*	0.1859
Brick construction	−0.2784*	0.0411	−0.2996*	0.0487
Basement	−0.1840*	0.0487	−0.2166*	0.0563
Basement is finished	0.0423	0.0436	0.0525	0.0485
Fireplace	−0.2596*	0.0757	−0.3060*	0.0886
Central air conditioning	−0.3649*	0.0708	−0.4093*	0.0827
One-car garage	−0.0578	0.0537	−0.0574	0.0597
Two-car garage (or more)	−0.0786**	0.0417	−0.0905**	0.0467
Garage is attached	0.1014	0.1024	0.0032	0.1219
Multi-family building	0.1841*	0.0493	0.2159*	0.0572
Lakeview	−0.3936*	0.0946	−0.4116*	0.1077
Logan Square	−0.6663*	0.0996	−0.6610*	0.1185
North Center	−0.5029*	0.0934	−0.4944*	0.1090
West Town	−0.2955*	0.1103	−0.2849*	0.1220
Ward 1	0.3790*	0.1142	0.4284*	0.1278
Ward 26	0.2134*	0.0981	0.2015**	0.1100
Ward 27	0.4428*	0.1697	0.5233*	0.1912
Ward 32	0.6530*	0.0693	0.7402*	0.0895
Ward 35	−0.4572*	0.1183	−0.7055*	0.1840
Ward 43	0.7267*	0.1125	0.8620*	0.1371
Ward 44	0.9276*	0.0951	1.0163*	0.1268
Constant	−3.2415*	0.9725	−5.8998*	1.2360
α_0			0.0087*	0.0029
α_1			0.0339	0.1099
Log-likelihood	−3235.1834		−3215.3801	

Notes. The number of observations is 9912, of which 1438 are teardown properties. The base community area is Lincoln Park. The base wards (31, 46, and 47) are on the perimeter of the sample area.

* Significance at the 1% level.

** Idem, 5%.

bricks, or has a basement, fireplace, or central air conditioning. The presence of each of these characteristics reduces the probability of demolition. Both community areas and wards have significant effects on teardown probabilities.

Table 3 indicates that there are statistically significant but small probabilities of misclassification in the Chicago data. The probability that a non-teardown is actually classified as a teardown (α_0) is statistically significant but small at 0.87%. The probability that a teardown is actually classified as a non-teardown (α_1) is not statistically significant. Other results are very similar across the two specifications.

Table 4
Probit models of teardown probabilities: six suburbs

Variable	Standard probit		Misclassification model	
	Coef.	Std. Err.	Coef.	Std. Err.
Distance from commuter train station	−0.2153*	0.0732	−0.3037*	0.1124
Within 1/2 mile of Lake Michigan	0.1898*	0.0747	0.2818*	0.1183
Within one block of rail line	−0.2552*	0.0960	−0.3742*	0.1482
Log of land area	−0.0977	0.1791	−0.1163	0.3351
Log of building density	−1.0740*	0.2052	−1.6385*	0.4396
Age in 1997	0.0009	0.0027	0.0013	0.0039
Land area relative to tract average	−0.0642	0.1042	−0.1253	0.1721
Building area relative to tract average	−0.1672	0.2189	−0.2595	0.4570
Age relative to tract average	0.1062	0.1353	0.1784	0.2034
Brick construction	−0.2149*	0.0528	−0.3027*	0.0855
Basement	−0.4874*	0.0729	−0.7638*	0.1686
Basement is finished	−0.0454	0.0503	−0.0492	0.0716
Fireplace	−0.0509	0.0529	−0.0467	0.0780
Central air conditioning	−0.0543	0.0488	−0.0646	0.0703
One-car garage	0.0952	0.0871	0.1470	0.1294
Two-car garage (or more)	−0.0047	0.0827	−0.0292	0.1227
Garage is attached	−0.0555	0.0539	−0.0919	0.0808
Kenilworth	−0.1896	0.1327	−0.2441	0.1910
Park Ridge	−0.5461*	0.1071	−0.7632*	0.1865
Western Springs	−0.3767*	0.1031	−0.5249*	0.1719
Wilmette	−0.3542*	0.0948	−0.5092*	0.1524
Winnetka	0.0006	0.0757	0.0169	0.1185
Constant	−1.0468	1.2750	−0.8501	2.3095
α_0			0.0054	0.0038
α_1			0.5003*	0.0900
Log-likelihood	−2184.8618		−2181.2179	

Notes. The number of observations is 7794, of which 789 are teardown properties. Glencoe is the base suburb.
* Significance at the 1% level.
** Idem, 5%.

Table 4 presents the probit results for the six suburbs. Again we find that demolition permits are more likely to be issued for properties near Lake Michigan and close to public transportation—in the suburban case, for commuter train stations rather than El stops. Buildings with low floor-area ratios are more likely to be demolished. However, relative measures of land area, building area, and age are statistically insignificant. The only structural characteristics that influence teardown probabilities are indicators of brick construction and the presence of a basement: houses with these characteristics are less likely to be demolished than others. Other things being equal, teardown probabilities are lower in Park Ridge, Western Springs, and Wilmette than in Glencoe and Winnetka, with Kenilworth forming a middle ground.

The results of the misclassification model indicate that about half (50.03%) of the observations that are classified as non-teardowns actually are misclassified in the sense that they behave similarly to the teardown sample. This result indicates the extent of the teardown phenomenon in these suburban communities. These suburbs are under severe redevelopment pressure. As the communities are rebuilt, existing homes are sold primarily for the land upon which they rest—even when a demolition permit is not observed for the house. The pervasiveness of the teardown phenomenon also likely accounts for the lack of explanatory power of variables representing age, land area, and building area relative to their census tract averages. When demolition permits actually have been issued for 10% of the properties and another 50% are probable teardowns, developers are no longer being particularly selective in the properties they choose for demolition. Even properties that are not purchased for immediate teardown are valued for their location and the opportunity to redevelop or renovate in the near future.

These results for Chicago and its suburbs have important implications for our land valuation models. It is not difficult to estimate land values in newer areas with ample open space. Land sales can easily be used to estimate land values in areas with many vacant lots. Although vacant lots seldom come up for sale in built-up, older areas, our probit results suggest that these areas are the ones where teardown activity is most widespread. Thus, teardowns have the potential to significantly increase the accuracy of land-value estimates in built-up areas.

6. Hedonic sales price models

The hedonic sales price models are presented in Tables 5–8. Three sets of results are presented in each table. The first set presents the results of simple regressions with no adjustments for selection bias. The second set of results presents the results with selection bias corrections based on the standard probit model, while the selection bias correction variable in the third set of results is based on the misclassification probit models. For the models with standard selection bias corrections, the teardown and non-teardown models are estimated separately using Eqs. (4) and (5). The teardown and non-teardown models are estimated jointly using Eq. (13) when the selection bias correction is based on the misclassification probit models.

Most of the results for the non-teardown models (Tables 5 and 7) are familiar. Sales prices tend to be higher near El stops and commuter train stations, closer to Lake Michigan, and when a property is more than a block from a railroad line. Large homes on large lots command higher sales prices. Sales prices are higher for homes made of brick and that have basements, fireplaces, central air conditioning, and garages. The R^2s for the models without selection bias correction variables are respectable: 0.7403 for the Chicago data and 0.8224 in the suburbs. The selection bias correction variables are significant for the non-teardown models in both Chicago and the suburbs. Correcting for selection bias generally does not qualitatively affect the results for the non-teardown samples. F-tests for joint significance of the estimates for the structural characteristics (indicated by italics in the tables) reject the null hypothesis that these coefficients jointly equal zero.

The results are much different for the teardown models, which are estimated using sales of properties for which demolition permits were issued in one of the two years after the sale. The Chicago results for teardown sales are presented in Table 6, while the suburban results are presented in Table 8. In general, fewer coefficients are statistically significant in the teardown equations. F-tests (not shown in the table) indicate that the locational and time of sale variables are jointly significant. In contrast, the structural variables do not offer significant explanatory power for the sales prices of teardown properties. Thus, our results provide strong support for the theoretical prediction that the sales price of a teardown property reflects its land value rather than any of the characteristics of the structure.

The pattern of results for the F-tests across model specifications shows the value of correcting for selection bias and misclassification of the dependent variables in the first-stage probit model. The F-tests for the set of structural variables are statistically significant when the selection bias correction variables are omitted from the equations. The value of the F-tests falls to insignificance when either the standard or misclassification selection bias correction variables are

Table 5
Non-teardown sales prices in Chicago

Variable	No selection correction		Standard probit selection correction		Misclassification selection correction	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Distance from nearest El Stop	−0.4519*	0.0184	−0.4172*	0.0197	−0.4225*	0.0194
Within 1/2 mile of Lake Michigan	0.0919*	0.0249	0.0836*	0.0250	0.0837*	0.0252
Within one block of rail line	−0.0789*	0.0090	−0.0794*	0.0089	−0.0799*	0.0090
Log of land area	0.2660*	0.0204	0.2056*	0.0251	0.2034*	0.0240
Log of building area	0.4315*	0.0124	0.4928*	0.0197	0.4915*	0.0182
Age in 1997	0.0001	0.0002	−0.0002	0.0002	−0.0001	0.0002
Brick construction	0.0939*	0.0087	0.1131*	0.0094	0.1103*	0.0092
Basement	0.0512*	0.0106	0.0625*	0.0111	0.0633*	0.0111
Basement is finished	0.0088	0.0090	0.0055	0.0090	0.0056	0.0090
Fireplace	0.0578*	0.0130	0.0765*	0.0141	0.0754*	0.0139
Central air conditioning	0.0983*	0.0131	0.1225*	0.0141	0.1199*	0.0138
One-car garage	0.0091	0.0115	0.0139	0.0114	0.0128	0.0115
Two-car garage (or more)	0.0600*	0.0091	0.0636*	0.0091	0.0637*	0.0091
Garage is attached	0.0515*	0.0171	0.0379*	0.0175	0.0396*	0.0174
Multi-family building	−0.1314*	0.0111	−0.1417*	0.0112	−0.1419*	0.0113
Lakeview	−0.1745*	0.0193	−0.1399*	0.0211	−0.1419*	0.0207
Logan Square	−0.4834*	0.0186	−0.4267*	0.0231	−0.4326*	0.0219
North Center	−0.3203*	0.0178	−0.2742*	0.0210	−0.2771*	0.0202
West Town	−0.4558*	0.0223	−0.4206*	0.0241	−0.4242*	0.0238
Ward 1	−0.0496*	0.0233	−0.0718*	0.0236	−0.0695*	0.0237
Ward 26	−0.1795*	0.0182	−0.1891*	0.0184	−0.1853*	0.0184
Ward 27	0.1253*	0.0337	0.0967*	0.0341	0.1045*	0.0342
Ward 32	0.2145*	0.0118	0.1738*	0.0152	0.1775*	0.0144
Ward 35	−0.2973*	0.0166	−0.2818*	0.0169	−0.2803*	0.0169
Ward 43	0.2708*	0.0212	0.2365*	0.0228	0.2362*	0.0225
Ward 44	0.1923*	0.0175	0.1326*	0.0225	0.1352*	0.0212
1996	0.1096*	0.0141	0.1096*	0.0142	0.1086*	0.0143
1997	0.2366*	0.0133	0.2354*	0.0134	0.2349*	0.0135
1998	0.3686*	0.0137	0.3672*	0.0137	0.3648*	0.0138
1999	0.5275*	0.0137	0.5269*	0.0137	0.5252*	0.0138
2000	0.7091*	0.0141	0.7082*	0.0141	0.7069*	0.0142
2001	0.7971*	0.0166	0.7968*	0.0165	0.7949*	0.0166
2002	0.8498*	0.0161	0.8495*	0.0160	0.8474*	0.0161
Selection bias correction			−0.2394*	0.0527	−0.2167*	0.0429
Constant	7.1016*	0.1435	7.0378*	0.1309	7.0753*	0.1316
R^2	0.7403		0.7413			
F-test, structural characteristics	237.4*		82.31*		97.17*	

Notes. Standard errors are calculated using a White [24] covariance matrix. Structural characteristics are indicated by italics. The number of observations is 8474. The model with a selection bias correction from the misclassification probit model is estimated jointly with its teardown counterpart in Table 6.

* Significance at the 1% level.
** Idem, 5%.

Table 6
Teardown sales prices in Chicago

Variable	No selection correction		Standard probit selection correction		Misclassification selection correction	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Distance from nearest El Stop	0.0024	0.1355	−0.2303	0.1674	−0.0699	0.1492
Within 1/2 mile of Lake Michigan	0.3106*	0.1281	0.4063*	0.1229	0.3431*	0.1234
Within one block of rail line	0.0704	0.0441	0.0560	0.0448	0.0640	0.0405
Log of land area	0.5191*	0.1244	1.0695*	0.2594	1.0157*	0.2522
Log of building area	0.1907*	0.0759	−0.2532	0.2204	−0.0945	0.2165
Age in 1997	0.0003	0.0013	0.0038**	0.0019	0.0030	0.0019
Brick construction	0.1332*	0.0661	0.0167	0.0868	0.0656	0.0780
Basement	−0.0656	0.0712	−0.1396**	0.0817	−0.1031	0.0788
Basement is finished	0.0300	0.0469	0.0448	0.0473	0.0296	0.0433
Fireplace	0.1322	0.0934	−0.0050	0.1086	0.0521	0.0990
Central air conditioning	0.0753	0.0563	−0.0746	0.0871	0.0187	0.0867
One-car garage	0.0380	0.0618	0.0217	0.0618	0.0343	0.0568
Two-car garage (or more)	−0.0046	0.0475	−0.0312	0.0489	−0.0316	0.0445
Garage is attached	0.1180	0.0836	0.1202	0.0780	−0.0304	0.0725
Multi-family building	−0.0420	0.0565	0.0383	0.0672	0.0241	0.0654
Lakeview	−0.3116*	0.0753	−0.4970*	0.1132	−0.3772*	0.1013
Logan Square	−0.5797*	0.0993	−0.8691*	0.1768	−0.6228*	0.1666
North Center	−0.4892*	0.0810	−0.7164*	0.1418	−0.5688*	0.1295
West Town	−0.5390*	0.1221	−0.6491*	0.1343	−0.5037*	0.1275
Ward 1	−0.0432	0.1430	0.0499	0.1516	−0.0713	0.1443
Ward 26	−0.2012	0.1332	−0.1642	0.1319	−0.2778*	0.1326
Ward 27	−0.4681*	0.2022	−0.4413*	0.2042	−0.6703*	0.2367
Ward 32	0.2210*	0.0869	0.4841*	0.1506	0.3316*	0.1451
Ward 35	0.6503*	0.1352	0.3486**	0.1901	1.3144*	0.2729
Ward 43	0.3869*	0.1100	0.7035*	0.1721	0.6234*	0.1669
Ward 44	0.4323*	0.1003	0.8057*	0.2023	0.4887*	0.1935
1996	0.3081*	0.0788	0.2922*	0.0748	0.2993*	0.0723
1997	0.2808*	0.0803	0.2758*	0.0783	0.3051*	0.0719
1998	0.5868*	0.0761	0.5869*	0.0737	0.6434*	0.0680
1999	0.7563*	0.0715	0.7514*	0.0687	0.7970*	0.0657
2000	0.9097*	0.0676	0.9025*	0.0650	0.9372*	0.0614
2001	1.0263*	0.0898	1.0030*	0.0851	1.0538*	0.0756
2002	1.0091*	0.0876	0.9952*	0.0819	1.0733*	0.0818
Selection bias correction			0.5809*	0.2706	0.2518	0.2410
Constant	6.4038*	1.0469	4.2665*	1.2214	3.8760*	1.1220
R^2	0.8782		0.8819			
F-test, structural characteristics	3.10*		0.87		1.04	

Notes. Standard errors are calculated using a White [24] covariance matrix. Structural characteristics are indicated by italics. The number of observations is 155. The model with a selection bias correction from the misclassification probit model is estimated jointly with its non-teardown counterpart in Table 5.

* Significance at the 1% level.

** Idem, 5%.

Table 7
Non-teardown sales prices in suburbs

Variable	No selection correction		Standard probit selection correction		Misclassification selection correction	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Distance from nearest commuter train station	−0.1321*	0.0077	−0.1165*	0.0079	−0.1118*	0.0088
Within 1/2 mile of Lake Michigan	0.1597*	0.0106	0.1337*	0.0110	0.1533*	0.0138
Within one block of rail line	−0.1060*	0.0118	−0.0786*	0.0123	−0.0734*	0.0139
Log of land area	0.3024*	0.0091	0.2244*	0.0136	0.2113*	0.0151
Log of building area	0.6034*	0.0114	0.7188*	0.0191	0.7391*	0.0222
Age in 1997	0.0011*	0.0002	0.0011*	0.0002	0.0014*	0.0003
Brick construction	0.0171*	0.0080	0.0455*	0.0087	0.0434*	0.0108
Basement	0.0695*	0.0125	0.1326*	0.0150	0.1274*	0.0194
Basement is finished	0.0327*	0.0060	0.0403*	0.0061	0.0371*	0.0069
Fireplace	0.0606*	0.0067	0.0627*	0.0067	0.0578*	0.0077
Central air conditioning	0.0156*	0.0061	0.0194*	0.0061	0.0227*	0.0069
One-car garage	0.0255*	0.0120	0.0206**	0.0118	0.0373*	0.0131
Two-car garage (or more)	0.0519*	0.0113	0.0570*	0.0112	0.0735*	0.0125
Garage is attached	−0.0002	0.0072	0.0035	0.0072	0.0035	0.0083
Kenilworth	0.2306*	0.0185	0.2627*	0.0190	0.2316*	0.0229
Park Ridge	−0.1338*	0.0128	−0.0637*	0.0159	−0.0825*	0.0202
Western Springs	−0.2053*	0.0138	−0.1499*	0.0157	−0.1648*	0.0200
Wilmette	0.0676*	0.0129	0.1227*	0.0148	0.1067*	0.0192
Winnetka	0.1486*	0.0138	0.1549*	0.0137	0.1332*	0.0184
1996	0.0521*	0.0104	0.0531*	0.0104	0.0482*	0.0131
1997	0.1109*	0.0100	0.1107*	0.0100	0.1142*	0.0125
1998	0.1835*	0.0098	0.1833*	0.0098	0.1776*	0.0122
1999	0.2670*	0.0103	0.2675*	0.0103	0.2529*	0.0127
2000	0.3792*	0.0113	0.3783*	0.0112	0.3617*	0.0134
2001	0.4425*	0.0148	0.4416*	0.0147	0.4096*	0.0168
2002	0.5159*	0.0148	0.5155*	0.0147	0.4835*	0.0166
Selection bias correction			−0.4148*	0.0586	−0.2964*	0.0439
Constant	5.2567*	0.1003	4.8832*	0.1101	4.8497*	0.1342
R^2	0.8224		0.8243			
F-test, structural characteristics	387.61*		197.64*		165.82*	

Notes. Standard errors are calculated using a White [24] covariance matrix. Structural characteristics are indicated by italics. The number of observations is 7005. The model with a selection bias correction from the misclassification probit model is estimated jointly with its teardown counterpart in Table 8.

* Significance at the 1% level.
** Idem, 5%.

added to the equation. Coefficients tend to fall toward zero when selection bias correction variables are added to the equations. Standard errors increase modestly in the non-teardown sample, but the increase in standard errors is sometimes large in the much smaller teardown samples. In the Chicago sample of teardowns, the only structural characteristics that achieve statistical significance at the 5% level are building area and brick construction in the model with no correction for selection bias. In both the Chicago and suburban teardown samples, no structural variable is significant at the 5% level once the estimates are adjusted for selection bias. The results overwhelmingly suggest that structural characteristics do not influence teardown sales prices.

Table 8
Teardown sales prices in suburbs

Variable	No selection correction		Standard probit selection correction		Misclassification selection correction	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Distance from nearest commuter train station	−0.1047*	0.0496	−0.1082	0.0906	−0.2146*	0.0525
Within 1/2 mile of Lake Michigan	0.1653*	0.0626	0.1693	0.1156	0.1733*	0.0573
Within one block of rail line	−0.1440	0.0886	−0.1479	0.1315	−0.2424*	0.0845
Log of land area	0.5112*	0.0510	0.5278	0.4141	0.7749*	0.1709
Log of building area	0.3569*	0.0682	0.3349	0.5446	−0.0339	0.2235
Age in 1997	−0.0003	0.0009	−0.0003	0.0014	−0.0002	0.0010
Brick construction	0.0176	0.0327	0.0135	0.1076	−0.0546	0.0495
Basement	0.1044*	0.0503	0.0952	0.2370	−0.0485	0.1081
Basement is finished	0.0314	0.0414	0.0305	0.0481	0.0539	0.0380
Fireplace	0.0213	0.0378	0.0203	0.0455	0.0561	0.0344
Central air conditioning	−0.0169	0.0350	−0.0177	0.0399	−0.0351	0.0305
One-car garage	−0.0337	0.0542	−0.0318	0.0711	−0.0657	0.0558
Two-car garage (or more)	−0.0604	0.0544	−0.0606	0.0547	−0.0841	0.0519
Garage is attached	0.0141	0.0351	0.0132	0.0425	−0.0260	0.0353
Kenilworth	0.3010*	0.0800	0.2973*	0.1192	0.2842*	0.0739
Park Ridge	−0.1257**	0.0647	−0.1373	0.2972	−0.2784*	0.1263
Western Springs	−0.2118*	0.0665	−0.2203	0.2144	−0.3534*	0.0907
Wilmette	−0.0191	0.0919	−0.0269	0.2259	−0.1058	0.1043
Winnetka	0.2706*	0.0460	0.2704*	0.0460	0.2268*	0.0411
1996	0.1069	0.1046	0.1077	0.1077	0.1118**	0.0572
1997	0.1593	0.1125	0.1604	0.1167	0.1135*	0.0565
1998	0.2276**	0.1198	0.2289**	0.1245	0.2323*	0.0604
1999	0.3516*	0.1181	0.3527*	0.1251	0.3842*	0.0622
2000	0.4632*	0.1067	0.4646*	0.1132	0.5206*	0.0581
2001	0.5953*	0.1203	0.5964*	0.1248	0.7130*	0.0825
2002	0.6800*	0.1145	0.6810*	0.1191	0.7671*	0.0685
Selection bias correction			0.0241	0.5807	0.2236	0.1962
Constant	5.0837*	0.5088	5.0705*	0.6027	5.5969*	0.3718
R^2	0.8678		0.8678			
F-test, structural characteristics	4.22*		0.89		1.11	

Notes. Standard errors are calculated using a White [24] covariance matrix. Structural characteristics are indicated by italics. The number of observations is 184. The model with a selection bias correction from the misclassification probit model is estimated jointly with its non-teardown counterpart in Table 7.

* Significance at the 1% level.

** Idem, 5%.

7. Conclusion

Teardowns are an important phenomenon in urban areas nationwide. Theoretical models of urban redevelopment imply that sales prices of homes that are about to be torn down should be a function only of structural characteristics. Our data set is unique in that it includes important structural characteristics for both standard home sales and sales of houses for which demolition permits are later issued. The results strongly support these predictions for sales of homes in the Chicago metropolitan area. After controlling for selection bias, structural variables do not provide statistically significant explanatory power in empirical models of sales prices of homes that are purchased as teardowns.

Teardown status may be subject to misclassification. While we use demolition permits to identify potential teardowns, obtaining a permit does not automatically imply that a structure is demolished. Other homes are so extensively remodeled that they are equivalent to new, even though a demolition permit was not required for the replacement. Furthermore, sales prices in active teardown markets may be determined primarily by the value of the location due to the expectation that these homes will be demolished or renovated in the near future. We use a technique proposed by Hausman, Arbrevaya, and Scott-Morton [8] to control for misclassification in our first-stage model of stage probit model of teardown status. Estimated models provide significant evidence of misclassification, particularly in active suburban teardowns markets. We use the misclassification probit model to control for selection bias in second-stage housing price regressions. Controlling for misclassification leads to stronger support for the predication that the sales prices of teardowns reflect only the value of the land.

Teardowns have proved to be controversial. New homes, which are often built to the limits of building codes and zoning regulations, can dwarf neighboring homes. New construction is disruptive and rapidly rising prices lead to higher tax bills for existing residents. However, teardowns also may help curb urban sprawl by allowing people who prefer to live in new housing to build in central areas, and a higher tax base can help increase services and reduce the rate of growth in tax rates over time. Our model suggests that the teardown market can be modeled accurately with a simple empirical model. The probit models imply that teardowns follow predictable patterns. Prime teardown candidates are small, older, homes near public transportation and the traditional village centers that surround commuter train stops. Hedonic sales price models have ample explanatory power, and strongly support the prediction that structural characteristics do not affect the price of a home that is about to be torn down. Thus, the price of a teardown accurately reflects land value in these locations.

Our results also have implications for assessors. It often is difficult to assess the value of land in built-up urban areas because few vacant lots are left. The small number of vacant lots that are left may be vacant for a reason, and their sales prices may not be an accurate reflection of land values for lots with structures. Teardown sales provide an alternative means of estimating land values in high-demand, built-up areas in which older buildings are being replaced with new construction.

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