Teardowns and Hedonic Land Value Function Estimation using Non-Sample Information

Daniel P. McMillen

© 2008 Lincoln Institute of Land Policy

Lincoln Institute of Land Policy
Working Paper

The findings and conclusions of this paper are not subject to detailed review and do not necessarily reflect the official views and policies of the Lincoln Institute of Land Policy.

Please do not photocopy without permission of the Institute.
Contact the Institute directly with all questions or requests for permission.

Lincoln Institute Product Code: WP08DM1

Abstract

Teardowns provide direct information on land values in fully developed urban areas because such properties are valued only for their land and location rather than for the characteristics of the structure. Stein-like procedures make efficient use of limited data when a group of variables – the structural characteristics – are expected beforehand to provide little explanatory power. Using data from Chicago for 1995-2003, this study shows how Stein-like rules based on both standard OLS regressions and two-stage selection models can be used to improve land value estimation.

About the Author

Daniel P. McMillen is a Professor in the Department of Economics at the University of Illinois at Chicago. He also is a visiting fellow at the Lincoln Institute of Land Policy and a consultant at the Federal Reserve Bank of Chicago. He served as the Director of the Center for Urban Real Estate at UIC from 1999-2005, and has been a member of the economics departments at the University of Oregon, Santa Clara University, and Tulane University. Professor McMillen received his Ph.D. in Economics from Northwestern University in 1987. His publications have appeared in such academic journals as the Journal of Urban Economics, Regional Science and Urban Economics, the Review of Economics and Statistics, Real Estate Economics, and the Journal of Business and Economic Statistics. He serves on the editorial boards of the Journal of Urban Economics, Real Estate Economics, Growth and Change, Journal of Housing Economics, Journal of Real Estate Literature, the Journal of Economic Geography, and the Journal of Regional Science.

Dr. Daniel P. McMillen
601 South Morgan MC144
University of Illinois at Chicago,
Chicago, IL 60607

telephone: (312) 413-2100
fax: 312-996-3344
email: mcmillen@uic.edu.

Acknowledgments. I thank Carter Hill and Richard Dye for comments and suggestions. The Lincoln Institute of Land Policy provided funding support for the project.

Table of Contents

Teardowns and Hedonic Land Value Function Estimation using Non-Sample Information

1. Introduction

Land values are a critical component of urban economic theory. As developed by Alonso (1964), Muth (1969), and Mills (1972), the standard monocentric city model implies that the value of access to the workplace is capitalized directly into land values. Land values guide the conversion of land from agriculture to use, the redevelopment of urban land to alternative uses, and the timing of land developments (Braid, 2001; Brueckner, 1980; Wheaton, 1982). Restrictive zoning practices can lead to sharp increases in land values in jurisdictions where land becomes difficult to develop. Studies such as Cheshire and Sheppard (2002) and Glaeser, Gyourko, and Saks (2005) make use of land values to measure the extent to which zoning alters market outcomes. Though accurate measures of land values are necessary to test many of the implications of urban economic theory, a lack of good data sources for land values has led empirical researchers to devote more attention to testing the models' implications for such variables as population density and house prices.

The ability to measure land values accurately also has immense practical importance. In many jurisdictions, assessors are required to provide separate assessments for structures and land. Differential tax rates for land and structures have been proposed since the time of Henry George, and have been employed in Pennsylvania with some success (Oates and Schwab, 1997). Since the supply of land is close to perfectly inelastic, a land tax could potentially be an attractive substitute for a more conventional property tax (England, 2003). Successful implementation of a land tax has been impeded by doubts concerning the accuracy of current assessment practices for land values.

Land values are difficult to measure in urban areas in part because vacant land sales are not common. Sales of vacant land are often concentrated in a small number of places and may be unrepresentative of the overall market. Nevertheless, many researchers have used vacant land sales to estimate land values in urban areas. Examples include Colwell and Munneke (1997), Thorsnes (1997), Cunningham (2006), and Ihlanfeldt (2007). Other researchers have attempted to use sales prices of developed properties to estimate land values. After controlling for the effects of structural characteristics, land value is treated either as a residual or is estimated directly from the coefficients for land area and various location characteristics (e.g., Jackson, Johnson, and Kaserman, 1984; Cheshire and Sheppard, 1995; Glaeser, Gyourko, and Saks, 2005).

Land values are difficult to estimate accurately using hedonic price functions because it is impossible to control completely for the myriad characteristics that influence a property's sales price. Consider the difficult to measure but critical structural characteristic, *quality*. Well-built, high-quality properties will tend to be concentrated in expensive neighborhoods with high-priced land. Although variables such as building area and the presence of pools and multi-car garages are correlated with structural quality, the list of measurable variables will always be incomplete. Since quality is correlated with land value, some of the effects of these variables will be attributed to the value of land. Hedonic estimates of land value will tend to be biased upward in desirable areas when this critical variable is missing.

Teardowns – properties that are demolished shortly after being purchased – offer another attractive data source for estimating land values in built-up urban areas. As noted by Rosenthal and Helsley (1994), the value of a teardown property is approximately equal to the value of the land on which it rests plus any demolition costs. Since demolition costs comprise a very small percentage of sales prices in areas where teardowns are common, teardowns can be a very useful tool for estimating land values in areas where vacant land is uncommon. Teardowns have been used to estimate land values in studies by Rosenthal and Helsley (1994), Munneke (1996), McGrath (2000), and Dye and McMillen (2007). An important implication of Rosenthal and Helsley's (1994) model is that only characteristics of the location should influence the sales price of teardown properties; structural characteristics should have little or no explanatory power. Dye and McMillen (2007) provide strong empirical support for this prediction. Missing structural variables do not result in biased coefficient estimates if they do not influence.

Although teardowns are more common in many cities than vacant land transactions, they are rarely as common as more conventional sales even in very active teardown markets. Relatively small samples increase the returns to efficient data use. Knight, Hill, and Sirmans (1993) propose a simple estimator that is nearly ideally suited to estimating land values using teardown properties. The idea is intuitive: if it is true that structural characteristics do not influence sales prices, then a regression estimate with these variables omitted should provide nearly the same explanatory power as an unrestricted regression that includes the structural variables. In practice, additional explanatory variables always provide some explanatory power even when the coefficients are statistically insignificant. Knight, Hill, and Sirmans show that a simple weighted average of the restricted and unrestricted estimates produces an estimator with such low variance that the estimates have lower mean squared errors in Monte Carlo experiments than simple OLS estimates even when some of the restrictions are actually false. This use of non-sample information – the theoretical prediction that structural characteristics have no effect on the sales prices of teardown properties – leads to little bias and much lower variance for the location variable coefficients.

Knight, Hill, and Sirmans refer to their formula for combining the restricted and unrestricted estimates as a "Stein-like" rule since it is an extension of Stein's (1956) estimator for the means of variables drawn from a multivariate normal distribution. The weights depend on the number of variables that are omitted to form the restricted regression and the value of the F-test used to determine whether the restrictions are actually at odds with the data. Higher values of the F-test lead to more weight being placed on the unrestricted estimates. This procedure works well in a standard regression context. However, there is strong reason to suspect that selection bias may affect simple regression estimates since teardown properties may not be drawn randomly from the full sample of properties. A modified version of the rule is needed that takes the sample selection rule into account.

Kim and Hill's (1995) analysis of a Box-Cox model can be adapted easily to the standard Heckman (1976) selection model. The "Heckit" estimator involves a first-stage probit model of the probability that a property is a teardown followed by a second-stage sales price regression that supplements the usual set of explanatory variables with a selection bias correction term. Kim and Hill's analysis implies that a weighted average of restricted and unrestricted second-stage estimates will produce an estimator with low mean squared error than standard Heckit estimates. The weights can be based on the log-likelihood values from joint estimation of the probit and regression models, or more simply on the Wald test statistics for a test that the structural variables add no explanatory power in the second-stage sales price regression.

While this application of the Stein approach significantly improves our ability to estimate land values accurately in built-up urban areas, it also has implications for other applications of the Heckman selection bias model. Although the Heckit estimator is formally identified by the nonlinearity of the bias correction variable, researchers generally try to identify the model as though it were a system of linear simultaneous equations. In the linear case, identification requires that some variable be omitted from the second-stage regression equation that is not included in the first-stage probit model. If a set of variables in the second-stage equation can be identified beforehand as having little or no influence on the dependent variable, then the Stein approach can potentially lead to significant reductions in the degree of variability that has plagued Heckit estimation.

The data set for the empirical section of the paper, which is drawn from sales of properties from an active teardown market in Chicago for 1995-2003, is an updated version of the data set used in Dye and McMillen (2007). As in the earlier paper, I find that structural characteristics have little influence on the sales prices of teardown properties. I then compare the estimates obtained from standard OLS, Heckit, and the Stein-like rule versions of each. Though the estimates of the coefficients for the location characteristics are similar across all four estimators, the Stein-like versions are closer to each other than are standard OLS and Heckit models. With only about 400 observations of teardown sales, the incorporation of non-sample information helps to improve the accuracy of the land value estimates drawn from the teardown sample.

2. The Stein Rule for OLS Estimation

The typical hedonic house price equation expresses the natural log of the sales price of a home (y) on a set of variables representing characteristics of the structure (S), location characteristics (L), and variables indicating the date of sale (D). Together, the full set of explanatory variables is $X = (1,S,L,D)$. The estimating equation is given by:

$$y_i = \beta_0 + S_i'\beta_S + L_i'\beta_L + D_i'\beta_D + e_i = X_i'\beta + e_i \qquad (1)$$

A teardown property is purchased exclusively for its lot. If demolition costs and salvage values are negligible, there should be no difference in the price of two adjacent properties on identical lots even if one has a 4000-square foot house in reasonably good condition while the other has a poorly maintained bungalow. If the properties are valuable simply because they each have, e.g., 10,000 square foot lots in desirable locations, then we can expect that $\beta_S = 0$ in a correctly specified equation. The estimated value of location – "land value" – is simply $L_i'\hat{\beta}_L$, i.e, the predicted value of the location characteristics.[1]

If the restriction $\beta_S = 0$ is correct, OLS estimation of equation (1) will, of course, provide unbiased estimates of β_L for teardown properties even though the a set of irrelevant variables is included in the regression. However, the variance of the estimates may be large, particularly since the S and L are likely to be correlated. For example, homes in areas with high land values may also tend to be small and old. Multicollinearity makes it difficult to entangle the separate effects of different explanatory variables even when some of the variables add little explanatory power. The restricted version of the model is a regression of y on L and D alone. If the omitted structural variables include J explanatory variables, then the F-test for $\beta_S = 0$ is based on a simple comparison of the residual sum of squares $(e_r'e_r)$ from this restricted regression and the residual sum of squares $(e'e)$ from the unrestricted model of equation (1). The test statistic is:

$$f = \frac{(e_r'e_r - e'e)/J}{e'e/(n-K)} \sim F(J, n-K) \qquad (2)$$

where n is the number of observations and K is the number of variables included in the unrestricted model.

In the classical modeling strategy, the final estimate of the parameter vector $\theta = (\beta_0 \quad \beta_L' \quad \beta_D')'$ would be θ_r if the F-test fails to reject the null hypothesis and θ_u if the F-test indicates that the structural characteristics add significant explanatory power to

[1] Cheshire and Sheppard (2002) estimate a version of this model in which the value of an additional square foot of lot area depends on location. Letting A indicate acreage and Z a set of indicators of location, their version of the model has, in effect, $L = AZ$. Thus, their estimating equation includes a series of interaction terms between lot size and the location variables. They refer to the marginal price of A as "land value," and their specification allows this price to vary spatially. While the approach taken here can easily be adapted to their specification, I will not draw a distinction between the value of land and the value of location.

the regression. In a series of Monte Carlo experiments, Knight, Hill, and Sirmans (1993) show that a weighted average of the two sets of parameter estimates has much lower mean squared error than standard OLS estimation. When there are at least three omitted variables in the restricted model $(J \geq 3)$, their starting point for the "Stein-like" rule combines the restricted and unrestricted estimates as follows:

$$\theta_s = \theta_u - \lambda(\theta_u - \theta_r) \tag{3}$$

where $\lambda = \frac{(J-2)}{n-K+2}\left(\frac{e'e}{e_r'e_r - e'e}\right) = \frac{(J-2)}{T-K+2}\left(\frac{T-K}{J}\right)\frac{1}{f}$. In practice, they find that a slight variation of this estimator works better in practice. This "positive-part variant" is

$$\theta_s^+ = \theta_u - 1.5\lambda(\theta_u - \theta_r) \text{ if } 1.5\lambda \leq 1$$
$$\theta_s^+ = \theta_r \text{ if } 1.5\lambda \leq 1 \tag{4}$$

In both versions of the rule, the weight placed on the unrestricted estimates θ_u increases with the value of the F-test statistic, f. The more likely it appears that the restrictions are correct – the lower is the value of f – the more weight is given to restricted estimates, θ_r.

Though the estimates θ_s and θ_s^+ are biased if $\beta_S \neq 0$, Knight, Hill, and Sirmans (1993) find that the mean squared error of these Stein estimators is much lower than the mean squared error for OLS even when the OLS model is correctly specified (i.e., when S is omitted from the regression and $\beta_s = 0$). Thus, the use of non-sample information – our expectation that the structural characteristics add little or no explanatory power to the hedonic price functions for teardown properties – allows us to construct estimates that have small bias and lower variance than standard OLS estimates.

Bootstrap procedures must be used to construct confidence intervals for θ_s or θ_s^+. In the empirical section of the paper, I use a simple bootstrap resampling procedure, drawing N combinations of y_i and X_i with replacement from the original matrices of values for the dependent variable and the explanatory variables. After 1000 repetitions of this resampling procedure, the bootstrap standard error estimates are simply the standard deviations of the 1000 new estimates of θ_s or θ_s^+.

3. A Stein-Like Rule for the Selection Bias Model

Selection bias is a potential concern in a study of teardowns because such properties are unlikely to be drawn randomly from the population of housing sales. For example, teardowns may be drawn from unusually low-quality structures in rapidly growing areas with high land values. The fact that the structures are of a lower quality than the population should cause little bias because structural characteristics – whether observed or relegated to the error term – will have little effect on sales prices. Unobserved location characteristics that make a property more likely to be a teardown are also likely to lead to high sales prices. To control for this form of selection bias, previous research (Rosenthal and Helsley, 1994; Munneke, 1996; McGrath, 2000; Dye and McMillen, 2007) has used the Heckman (1976) two-stage estimator. The first stage is a probit model predicting the probability that a property is a teardown as a function of a set of a set of explanatory variables, Z. The predicted probability, $\Phi\left(Z'\hat{\gamma}\right)$, is then used to form the selection bias correction variables, which are given by $\phi\left(Z'\hat{\gamma}\right)/\Phi\left(Z'\hat{\gamma}\right)$ for the teardown sample and $-\phi\left(Z'\hat{\gamma}\right)/\left(1-\Phi\left(Z'\hat{\gamma}\right)\right)$ for the non-teardown sample.

The Stein-rule approach's efficiency gain may have even more benefit for the selection model because the two-stage estimates are frequently found to be highly variable and sensitive to the model specification. It is difficult to find variables to include in the probit model that cannot also plausibly be considered for the second-stage regression. A Stein-like estimator may reduce the variability of the two-stage estimator if a list of variables can be specified that can reasonably be expected beforehand to have little predictive power in the second-stage regression estimates. In the case of teardowns, this non-sample information is readily available as the structural characteristics are predicted to have no explanatory power for sales prices. The Stein approach's reduction in variability is particularly important in a model of teardowns because it allows the limited number of observations to be used more efficiently to estimate the land values.

Kim and Hill (1995) develop a Stein-like rule for a nonlinear regression model that is based on a weighted average of restricted and unrestricted estimates. Although their estimator is developed in the context of a model with a Box-Cox transformation, it is straightforward to extend it to other models in which simple OLS regressions are inappropriate. The key is to have a chi-squared distributed test statistic for the set of exclusion restrictions. Wald, LaGrange multiplier, and likelihood ratio (LR) tests are all suitable for their estimator. Since exclusion restrictions are probably most likely to be tested using a Wald test in the standard two-stage selection model, I will assume that this test will be used to test whether *S* adds significant explanatory power to the second-stage sales price regressions.

Let μ represent the value of the Wald test statistic for a test that the structural characteristics add no explanatory power in the second-stage sales price regression. As before, let θ_u and θ_r represent the estimated coefficients for the sales price regression when the structural characteristics are include (*u*) and excluded (*r*). In the selection model, the vectors of estimated coefficients are expanded to include the coefficient for the selection bias correction variable, which is included in both the restricted and unrestricted regressions. Kim and Hill (1995) find that the following weighted average of the two sets of coefficients produces an estimator with low mean squared error:

$$\theta_s = \theta_r + I\left(\mu < 2(J-2)\right)\left(1-\frac{2\left(J-2\right)}{\mu}\right)\left(\theta_u - \theta_r\right) \qquad (5)$$

where $I(\bullet)$ is an indicator function and, as before, *J* is the number of coefficients constrained to equal zero in the restricted model. As in the case of OLS, this rule places more weight on the unrestricted estimates the greater is the value of the test statistic for the exclusion restrictions, μ.

In the empirical section of the paper, I use the covariance matrix estimate given in Greene (1981) to construct the Wald test. I again use a bootstrap procedure to construct standard errors for θ_s. Letting n_1 represent the number of teardown properties and n_2 the number of non-teardowns, each iteration of the bootstrap involves drawing n_1 combinations of y_i and X_i with replacement from the teardown sample and n_2 combinations with replacement from the non-teardown sample. I then re-estimate the full model – probit, second-stage sales price regressions, Wald tests, and the Stein-like rule of equitation (5) – for each bootstrap sample. The standard errors for θ_s are then simply the standard deviations of the 1000 new estimates of θ_S .

4. Data and Model Specification

The data set for the empirical analysis is drawn from three sources. Data for the sales price of small (1-6 unit) properties come from the Illinois Department of Revenue (IDOR). The IDOR data were then merged with the Cook County Assessor's file of property characteristics for 1997. This file includes data on standard explanatory variables for hedonic prices functions – age, square footage, and lot size; the presence of a basement, a fireplace, brick construction, a one-car garage, a larger garage; and indicators that the basement is finished, the garage is attached to the home, and that the home has 2-6 units rather than only one. Finally, demolition permit data were obtained from the City of Chicago to determine whether a property is a teardown. The data were then geo-coded to identify the neighborhood and ward for the property and to measure distance to Lake Michigan, the nearest stop on the elevated rapid transit line (EL), and the nearest freight or commuter train line.

I restrict the analysis to five neighborhoods on the near north side of Chicago, Lakeview, Lincoln Park, Logan Square, North Center, and West Town. Each of these neighborhoods has relatively high-priced and rapidly appreciating housing. The area is a hotbed of teardown activity. In order to accommodate new construction, older homes are routinely torn down by their owners or by developers. Vacant lots are rare.

In this environment, it is nearly certain that any home that is about to be demolished is also about to be replaced by a new home. Thus, the strategy of using demolition permits to identify teardowns runs little risk that we actually are identifying decaying buildings that are simply be demolished without an expectation that that they will be replaced by a new structure in the near future. In an earlier use of this data set, Dye and McMillen (2007) explicitly take into account the potential misclassification of teardown properties. They use Hausman, Arbrevaya, and Scott-Morton's (1998) procedure to estimate a probit model of teardown status that explicitly accounts for the probability that a teardown sale is classified incorrectly as a non-teardown and vice-versa. The probability that a teardown is incorrectly classified as a non-teardown is estimated to be a statistically insignificant 3.39%. The probability that a non-teardown is incorrectly classified as a teardown is a statistically significant but extremely small 0.87%. Based on these estimates, identifying teardowns through demolitions permits works well. In the estimated probit models of teardowns, the dependent variable has a value of one if a demolition permit was issued for the property between 1997 and 2004, and it will be classified as a non-teardown otherwise.[2]

The dependent variable for the second-stage regression is the natural log of sales price. The timing of the sales is critical when analyzing teardown properties. For example, if a sale takes place in 1994 and a demolition permit is issued 1998, was the property purchased originally as a teardown? Unless the permit application follows the sale quickly, the structural characteristics may have a significant effect on sales price. Thus, I follow Dye and McMillen (2007) and define a teardown sale as a sale taking place no more than two years prior to an application for a demolition permit.[3] If a property is recorded as having an application for a demolition permit with either no sale or a sale before or after the two-year interval prior to the application, the observations is classified as a teardown but the observation is not included in the second-stage sales price regressions. Thus, the number of teardowns is larger for the first-stage probit model than in the second-stage sales price regressions.[4] The final sample consists of two groups of properties: (1) teardown properties, defined as properties with a demolition permit issued sometime between 1995 and 2004; and (2) non-teardowns, defined as properties that never have had a demolition permit recorded and which sold sometime between 1995 and 2003 (the 2003 end period being chosen to correspond with the timing of the sales for teardown properties).[5]

Descriptive statistics are displayed in Table 1. Comparing the teardown and non-teardown samples, it is clear that teardowns are likely to be older and to have lower floor-area ratios. The sample of teardown properties with sales appears quite similar to the sample of properties that did not have a sale but which had demolition permit

[2] Dye and McMillen (2007) develop a version of the two-stage selection estimator that takes into account the probability that the dependent variable for the probit model is misclassified. Kim and Hill's (1995) Stein-like rule could readily be extended to this model using a Wald test for exclusion restrictions in the second-stage regression. Though they do find evidence of significant misclassification probabilities in suburban areas of Chicago, I chose to restrict the analysis to the standard Heckit procedure since the estimated probabilities are very close to zero in the city sample.

[3] In unreported results, Dye and McMillen's (2007) experiments with other cutoff dates – one year or three years – had little effect on the results. The advantage of a two-year cutoff is that it leads to more teardown sales than one year with little effect on the results, while a three-year cutoff appears sufficiently long that some properties are likely to be purchased without an expectation of pending demolition.

[4] The implicit assumption is that properties with demolition permit applications are drawn from the same population whether or not a sale is observed in the two-year window prior to the application. Some evidence that this assumption is acceptable is offered in the descriptive statistics. While it is possible to model the three groups (non-teardowns, properties with demolition permits and sales in the two-year windows, and other properties with demolition permits) separately, this extension is beyond the scope of the current paper.

[5] The assessment data all date from 1997 while sales dates range from 1995 to 2003. Since the date of the teardown sales always precedes the date of the demolition permit application, there is little risk that the structural characteristics for the teardown observations actually reflect subsequent new construction. However, assessment files are updated with some lag and there is some probability the structural characteristics are measured with error, particularly since only one year's assessment file is available for this analysis.

applications during this period. Note that a political division – the ward – is included along with Chicago's traditional neighborhood designation. I include this variable because Chicago's aldermen effectively have veto power over developments in the ward they represent. Since some aldermen are more receptive to teardowns than others, this variable is a potentially important determinant of teardown status.

Table 1 also show the classification of variables as structural characteristics (*S*), characteristics of the lot and location (*L*), and other characteristics included in the sales price regressions (namely, date of sale, *D*). The sales price models include these sets of characteristics as explanatory variables. The probit model of teardown status differs in several ways from the sales price regressions. First, the time of sale variables are omitted since these variables are not observed unless a property has actually sold. Second, the natural log of building area is replaced by the log of the floor area ratio – the ratio of building area to lot size, or FAR. Developers claim that the floor area ratio is an important determinant of teardown status because zoning provisions directly regulate density in Chicago. In addition, it is expensive to tear down tall buildings, while small lots make it difficult to maneuver when demolishing a building. Since perfect collinearity prevents the logs of land area, building area, and the floor area ratio from all being included in a regression, it seems reasonable to include FAR rather than building area in the probit model of teardown status. This modification of the explanatory variable list helps identify the model by providing an additional source of variation across the two equations.

Identification also is obtained by adding three variables that control for differences between a property and other buildings in the neighborhood. Developers may be more likely to choose older, smaller homes on large lots for demolition. Thus, I include the ratios of age, land area, and building areas to their census tract averages as explanatory variables for the probit models of teardown status.

5. Regression Results

Standard OLS regression results are shown in the first two sets of estimates in Table 2. The first set of results includes structural characteristics, characteristics of the location, and the year of sale as explanatory variables, while the second set of results comes from a restricted model in which the structural characteristics are omitted. Although an F-test suggests that the structural characteristics offer statistically significant explanatory power, only the estimated coefficients for building area and brick construction are significant at the 5% level in the unrestricted regression. In general, the structural characteristics have far less explanatory power than the location variables or the year of sale.

Since teardowns are valued primarily for their lot, land values can be inferred from the location variables. The results suggest that land values are higher close to EL stops and near Lake Michigan. Proximity to rail lines does not have a statistically significant effect on land values. The elasticity of land value with respect to lot size is estimated to be 0.5797 in the unrestricted regression, compared with 0.6666 in the regression with the structural characteristics omitted. Land values appreciated rapidly between 1995 and 2003. The estimated coefficient of 1.0012 for the unrestricted model implies that land values rose at an average annual rate of approximately 13.3% over this period, compared with 14.0% for the restricted model.

The last set of results in Table 2 is obtained from the Stein-like rule weighted average of the restricted and unrestricted regression estimates, as given by equation (4). Since the F-statistic is statistically significant, the rule places more weight (69.21%) on the unrestricted estimates than on the restricted estimates (λ = 30.79%). The estimated coefficients thus lie closer to their values from the unrestricted estimates, while the coefficient for the 2003 dummy variable (1.0158) implies an average annual rate of appreciation of 13.5%. The bootstrap standard errors are generally close to their OLS counterparts, with some variation. The high R^2's for both the restricted and unrestricted models suggest that land values can be estimated quite accurately using teardowns.

The Stein rule takes advantage of our prior expectation that structural characteristics have little effect on the sales prices of teardown properties. Table 3 provides some evidence about the sensitivity of the results to the specification of variables excluded from the restricted estimates. In particular, the log of building area and the dummy variable representing brick construction are included in the restricted regression since they are statistically significant in the unrestricted model. The value of λ increases to 0.7158 when these variables are included in the restricted estimates, meaning that under this specification the Stein-like estimator places 71.58% weight on the restricted estimates. The important feature of Table 3 is the remarkable similarity of the Stein estimator results under the two alternative specifications. For example, the coefficient for the log of lot size is 0.5797 in the unrestricted model, compare with 0.6666 in the original restricted specification. The Stein rule estimate is 0.6064 when building area and brick construction are counted as excluded variables in the restricted model, while the estimate is similar at 0.5811 for the Stein rule estimator with the alternative set of excluded regressors. These results suggest that the Stein rule approach does indeed reduce the variability of the land value estimates.

Some researchers have attempted to use hedonic price functions for non-teardown properties to estimate land values. Table 4 shows that the land value estimates implied by non-teardown sales are much different from the estimates obtained using teardowns. The coefficients for the structural characteristics are highly significant (F = 271.85), and the Stein rule only places a weight of 0.0045 and the restricted estimates. The difference between the land value estimates implied by the teardown and non-teardown samples is most evident in the estimated effects of lot size proximity to Lake Michigan. Whereas the teardown Stein-rule estimates imply that the elasticity of land value with respect to lot size is 0.6064, the estimated elasticity is only 0.2979 in the teardown sample. The Stein-rule coefficient for proximity to Lake Michigan is 0.5525 for the teardown sample, compared with a marginally significant 0.0641 in the non-teardown sample.

The likely reason for these differences is that the non-teardown sample attributes some of the effect of missing structural variables to location. For example, a home on a large lot may well prove to have a fairly low-quality structure since it is likely to have been built at a time when the location was in low demand. Since structural characteristics significantly influence the value of non-teardown homes, a missing variable that is positively correlated with lot size may lower the sales price. Thus, non-teardown sale prices attribute some of the effects of low-quality construction material to lot size. Teardowns are a much more accurate measure of land value because they suffer far less from missing variable bias caused by omitted structural characteristics. If structural characteristics have little effect on the sales price of teardown properties, then the fact that these variables are not measured accurately has little effect on the estimates for a sample of teardown properties.

6. Selection Model Results

The OLS results are subject to selection bias if teardowns are not drawn randomly from the full sample of sales. Previous research (Rosenthal and Helsley, 1994; Munneke, 1996; McGrath, 2000; and Dye and McMillen, 2007) has corrected for sample selection bias using the Heckman two-stage estimation procedure. This section presents the results of standard Heckit estimates, along with estimates of a Stein-rule version based on the results of Kim and Hill (1995).

The first-stage probit results are shown in Table 5. The dependent variable for the probit model equals one if a demolition permit was recorded for the property between 1995 and 2004. Although they have little direct influence on the sales price of teardown properties, structural characteristics have significant effects on the teardown probability. Measurably higher-quality homes – those with a basement, fireplace, central air conditioning, a garage, and brick construction – are significantly less likely to be demolished. However, homes in good locations – near Lake Michigan and close to an EL stop – are more likely to be torn down. Teardowns are also more likely for homes on large lots with low floor area ratios. Somewhat surprisingly, a home is more likely to be torn down when its lot is smaller than the average in a census tract. Teardowns also tend to be drawn from homes that are older than the average for the tract.

Table 6 shows the results of second-stage sales price regressions for the subset of properties with demolition permits that also were sold during the two years prior to the application. The results are directly comparable to the OLS results of Table 2. Although the selection bias correction variable is not statistically significant, including it in the regression leads to statistically insignificant coefficients for every structural characteristic variable. The coefficients for building area and brick construction decline markedly in value, which suggests that much of the apparent effect of these variables on land values is actually due to their role in determining whether a structure is torn down. The coefficients for the location variables tend to increase in magnitude after controlling for selection bias. The restricted second-stage Heckit estimates shown in Table 6 are quite similar to the restricted OLS estimates in Table 2 even though the selection bias correction variable adds significant explanatory power to the second-stage sales price regression. However, the Stein-rule estimates for the Heckit model differ from the Stein-rule OLS estimates because the Heckit version of the Stein rule places zero weight on the unrestricted estimates since the Wald test fails to reject the restricted model.

Table 7 shows the selection model results for the non-teardown properties. The selection-bias correction variable and the structural characteristics add significant explanatory power to these regressions, so the Stein-like rule places most (97.29%) of the weight on the unrestricted model. No matter which model is used, the estimated coefficients for the structural characteristics are much different from their counterparts in the teardown properties. The estimated value of location is likely to be subject to severe bias in a sample of developed properties whose value is determined in part by the value of the structure.

The Stein-like rule estimates shown in Table 6 are the preferred land value estimates. The estimates are not subject to bias from missing structural characteristics variables because teardown sales reflect the value of lot size and location alone. The two-stage estimation procedure controls for the selection bias that may be present if teardown properties are not randomly drawn from the general population. The Stein-rule version of the estimator removes the imprecision induced by the inclusion of insignificant structural characteristics. Furthermore, the Stein-rule helps to increase the precision of the two-stage Heckman procedure by ensuring that the teardown sales price model is identified by exclusion restrictions.

7. Conclusion

Teardowns are a useful tool for estimating land values in built-up urban areas. Since the prices of teardown properties are not influenced by any characteristics of the current structure, teardowns provide direct estimates of land value without any contaminating influences from unobserved structural characteristics. In this paper, I demonstrate how this non-sample information – our prior expectation that structural characteristics do not affect teardown sales prices – can be used to obtain more efficient estimates of land values in active teardown markets. A direct application of Knight, Hill, and Sirmans' (1993) version of the Stein suggests that a weighted average of the OLS estimates with and without the structural characteristics as explanatory variables produces an efficient set of land value estimates that suffer from little bias. The ability of this estimator to extract information efficiently from small samples is important since teardowns comprise a relatively small portion of the total number of sales even in active teardown markets.

The paper also shows how Kim and Hill's (1995) version of the Stein rule can be applied to hedonic price functions that include controls for selection bias. Selection bias is likely to be present when analyzing teardowns because teardowns are unlikely to be drawn randomly from the total sample of sales. This version of the Stein rule is based on the value of a Wald test statistic determining whether structural characteristics add significant explanatory power to the second-stage hedonic sales price function. The Stein rule has a further advantage in the context of the selection model because the standard two-stage estimation procedure suffers from multicollinearity and exclusion restrictions are not always readily available. The second-stage model will be estimated more precisely using a Stein-like estimator that places some weight on a model incorporating reasonable exclusion restrictions even if the excluded variables cannot definitively be ruled out of the model beforehand.

References

Alonso, William, *Location and Land Use*, Harvard University Press, Cambridge (1964).

Braid, Ralph M., "Spatial Growth and Redevelopment with Perfect Foresight and Durable Housing," *Journal of Urban Economics* 49 (2001), 425-452.

Brueckner, Jan K., "A Vintage Model of Urban Growth," *Journal of Urban Economics* 8 (1980), 389-402.

Cheshire, Paul and Stephen Sheppard, "The Price of Land and the Value of Amenities," *Economica* 62 (1995), 247-267.

Cheshire, Paul and Stephen Sheppard, "The Welfare Economics of Land Use Planning," *Journal of Urban Economics* 52 (2002), 242-269.

Colwell, Peter F. and Henry J. Munneke, "The Structure of Urban Land Prices," *Journal of Urban Economics* 41 (1997), 321-336.

Cunningham, Christopher R., "House Price Uncertainty, Timing of Development, and Vacant Land Prices: Evidence for Real Options in Seattle," *Journal of Urban Economics* 59 (2006), 1-31.

Dye, Richard F. and Daniel P. McMillen,, "Teardowns and Land Values in the Chicago Metropolitan Area," *Journal of Urban Economics* 61 (2007), 45-63.

England, Richard W., "State and Local Impacts of a Revenue-Neutral Shift from a Uniform Property to a Land Value Tax: Results of a Simulation Study," *Land Economics* 79 (2003), 38-43.

Glaeser, Edward L., Joseph Gyourko, and Raven E. Saks, "Why is Manhattan so Expensive? Regulation and the Rise in Housing Prices," *Journal of Law and Economics* 48 (2005), 331-370.

Greene, William H., "Sample Selection Bias as a Specification Error: A Comment," *Econometrica* 49 (1981), 795-798.

Hausman, J.A., Jason Arbrevaya, and F.M. Scott-Morton, "Misclassification of the Dependent Variable in a Discrete-Response Setting," *Journal of Econometrics* 87 (1998), 239-269.

Heckman, James J., "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models," *Annals of Economic and Social Measurement* 5 (1976), 475-492.

Ihlanfeldt, Keith R., “The Effect of Land Use Regulation on Housing and Land Prices,” *Journal of Urban Economics* 61 (2007), 420-435.

Jackson, Jerry R., Ruth C. Johnson, and David L. Kaserman, “The Measurement of Land Prices and the Elasticity of Substitution in Housing Production,” *Journal of Urban Economics* 16 (1984), 1-12.

Kim, Minbo and R. Carter Hill, “Shrinkage Estimation in Nonlinear Regression: The Box-Cox Transformation,” *Journal of Econometrics* 66 (1995), 1-33.

Knight, J.R., R. Carter Hill, and C.F. Sirmans, “Estimation of Hedonic Housing Price Models using Nonsample Information: A Monte Carlo Study,” *Journal of Urban Economics* 34 (1993), 319-346.

McGrath, Daniel T., “Urban Industrial Redevelopment and Contamination Risk,” *Journal of Urban Economics* 47 (2000), 414-442.

Mills, Edwin S., *Studies in the Structure of the Urban Economy*, Johns Hopkins University Press, Baltimore (1972).

Munneke, Henry J., “Redevelopment Decisions for Commercial and Industrial Properties,” *Journal of Urban Economics* 39 (1996), 229-253.

Muth, Richard, *Cities and Housing*, University of Chicago Press, Chicago (1969).

Oates, Wallace E. and Robert M. Schwab, “The Impact of Urban Land Taxation: The Pittsburgh Experience,” *National Tax Journal* 50 (1997), 1-21.

Rosenthal, Stuart S. and Robert W. Helsley, “Redevelopment and the Urban Land Price Gradient,” *Journal of Urban Economics* 35 (1994), 182-200.

Stein, C., “Inadmissibility of the Usual Estimator for the Mean of a Multivariate Normal Distribution,” in *Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability, Volume 1*, University of California Press, Berkeley (1956), 197-206.

Thorsnes, Paul, “Consistent Estimates of the Elasticity of Substitution between Land and Non-Land Inputs in the Production of Housing,” *Journal of Urban Economics* 42 (1997), 98-108.

Wheaton, William C., “Urban Residential Growth under Perfect Foresight,” *Journal of Urban Economics* 12 (1982), 1-21.

Table 1
Descriptive Statistics

	Teardowns, Sales (399 obs.)		Teardowns, No Sales (1961 obs.)		Non-Teardowns (11,064 obs.)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sales Price (1000s)	349.1720	226.5360			369.9460	1493.3740
Log of Sales Price	12.5801	0.6183			12.5892	0.6418
Structural Variables (*S*)						
Age in 1997	104.6491	13.7409	104.4549	13.9410	89.5444	31.4579
Basement	0.6967	0.4602	0.6808	0.4663	0.7394	0.4390
Basement is finished	0.2607	0.4395	0.2356	0.4245	0.2341	0.4234
Fireplace	0.0476	0.2132	0.0515	0.2211	0.1361	0.3429
Central air	0.0526	0.2236	0.0607	0.2388	0.1687	0.3745
Garage, 1-car	0.1830	0.3871	0.1657	0.3719	0.1907	0.3929
Garage, 2 or more cars	0.4486	0.4980	0.4804	0.4997	0.4847	0.4998
Garage is attached	0.0276	0.1639	0.0245	0.1546	0.0722	0.2589
Multi-family	0.5539	0.4977	0.5946	0.4911	0.6244	0.4843
Log of building area	7.3564	0.4382	7.4167	0.4573	7.6252	0.4592
Brick construction	0.3058	0.4613	0.3361	0.4725	0.5598	0.4964
Location Variables (*L*)						
Distance from EL stop	0.3958	0.2047	0.4053	0.2159	0.4522	0.2481
Near Lake Michigan	0.0075	0.0865	0.0178	0.1324	0.0140	0.1175
Near rail line	0.3609	0.4809	0.3748	0.4842	0.2975	0.4572
Log lot size	8.0700	0.2485	8.0749	0.2386	7.9811	0.3771
Lakeview	0.2306	0.4217	0.2723	0.4453	0.1734	0.3786
Logan Square	0.1278	0.3343	0.1275	0.3336	0.2801	0.4491
North Center	0.1779	0.3829	0.1775	0.3822	0.1705	0.3761
West Town	0.2581	0.4382	0.2228	0.4163	0.2215	0.4153
Ward 1	0.1554	0.3627	0.1300	0.3364	0.1245	0.3301
Ward 26	0.0677	0.2515	0.0658	0.2480	0.1116	0.3149
Ward 27	0.0100	0.0997	0.0229	0.1498	0.0218	0.1460
Ward 32	0.3734	0.4843	0.3565	0.4791	0.2570	0.4370
Ward 35	0.0175	0.1315	0.0265	0.1607	0.1307	0.3371
Ward 43	0.1579	0.3651	0.1326	0.3392	0.1142	0.3181
Ward 44	0.1103	0.3136	0.1673	0.3733	0.0925	0.2897
1996	0.0752	0.2640			0.1122	0.3156
Additional Variables for the Sales Price Regression (*D*)						
1997	0.1053	0.3073			0.1243	0.3299
1998	0.1303	0.3371			0.1207	0.3257
1999	0.2055	0.4046			0.1196	0.3245
2000	0.1228	0.3286			0.0913	0.2880

2001	0.0977	0.2973			0.1027	0.3035
2002	0.1178	0.3228			0.1083	0.3107
2003	0.1153	0.3198			0.1165	0.3208
Variables Included in the Probit Model that are Excluded from the Sale Price Regressions						
Log of floor area ratio (in place of building area)	-0.7136	0.4463	-0.6582	0.4610	-0.3559	0.5108
Land area divided by tract average	1.0624	0.2712	1.0565	0.2872	0.9666	1.2598
Building area divided by tract average	0.7368	0.3143	0.7786	0.3403	0.9761	0.4482
Age divided by tract average	1.1361	0.1971	1.1356	0.2205	0.9622	0.3462

Table 2
Regressions for Teardown Properties

	Unrestricted		Restricted		Stein-Like Rule	
Variable	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Age in 1997	0.0005	0.0012				
Basement	0.0579	0.0348				
Basement is finished	0.0197	0.0353				
Fireplace	0.0888	0.0757				
Central air	0.1247*	0.0730				
Garage, 1-car	-0.0482	0.0443				
Garage, 2 or more cars	-0.0305	0.0358				
Garage is attached	0.0618	0.0918				
Multi-family	-0.0534	0.0414				
Log of building area	0.1688**	0.0524				
Brick construction	0.1161**	0.0369				
Distance from EL stop	-0.3244***	0.0860	-0.4023***	0.0870	-0.3484***	0.0855
Near Lake Michigan	0.5008**	0.1794	0.6686***	0.1777	0.5525*	0.2491
Near rail line	0.0008	0.0342	-0.0135	0.0350	-0.0036	0.0314
Log lot size	0.5797***	0.0732	0.6666***	0.0706	0.6064***	0.0996
Lakeview	-0.2749***	0.0828	-0.3576***	0.0840	-0.3004***	0.0602
Logan Square	-0.6056***	0.0881	-0.6466***	0.0861	-0.6182***	0.0805
North Center	-0.4639***	0.0811	-0.5371***	0.0807	-0.4864***	0.0622
West Town	-0.7009***	0.0898	-0.7510***	0.0882	-0.7163***	0.1102
Ward 1	0.1289	0.0845	0.1050	0.0870	0.1215	0.1018
Ward 26	-0.2263**	0.0829	-0.2812**	0.0848	-0.2432*	0.1061
Ward 27	0.0348	0.1690	0.1905	0.1719	0.0828	0.1407
Ward 32	0.1937***	0.0580	0.1841**	0.0597	0.1908***	0.0486
Ward 35	-0.5436***	0.1366	-0.6072***	0.1378	-0.5632*	0.2327
Ward 43	0.2965**	0.0984	0.3157**	0.0998	0.3024***	0.0827
Ward 44	0.2542***	0.0726	0.2674***	0.0745	0.2583***	0.0526
1996	0.1184	0.1033	0.1700	0.1057	0.1343	0.1114
1997	0.0734	0.0983	0.1132	0.1001	0.0857	0.1052
1998	0.4220***	0.0965	0.4735***	0.0986	0.4378***	0.1047
1999	0.6245***	0.0944	0.6766***	0.0961	0.6406***	0.1007
2000	0.6993***	0.0965	0.7588***	0.0991	0.7176***	0.1096
2001	0.6650***	0.0995	0.7002***	0.1019	0.6758***	0.1332
2002	0.8272***	0.1000	0.8940***	0.1018	0.8478***	0.1083
2003	1.0012***	0.0973	1.0486***	0.0995	1.0158***	0.1067
Constant	6.3912***	0.6490	7.0645***	0.5988	6.5985***	0.8148
R^2	0.8058		0.7825		F(11, 364) = 3.96***	

Notes. The sample comprises 399 properties that sold within 2 years prior to the time a demolition permit was issued. The dependent variable is the natural log of sales price. Significance levels of 1%, 5%, and 10% are indicated by "***", "**", and "*". For the Stein-like estimator, λ = 0.3079.

Table 3
Regressions for Teardown Properties with Alternative List of Structural Variables

Variable	Unrestricted Model	Restricted Model, Original Specification		Building Area and Brick Omitted from Structural Variables	
		OLS	Stein	OLS	Stein
Log of building area	0.1688**			0.1398***	0.1480***
Brick construction	0.1161**			0.1205***	0.1192***
Distance from EL stop	-0.3244***	-0.4023***	-0.3484***	-0.3407***	-0.3361***
Near Lake Michigan	0.5008**	0.6686***	0.5525*	0.6086***	0.5779*
Near rail line	0.0008	-0.0135	-0.0036	-0.0013	-0.0007
Log lot size	0.5797***	0.6666***	0.6064***	0.5811***	0.5807***
Lakeview	-0.2749***	-0.3576***	-0.3004***	-0.3129***	-0.3021***
Logan Square	-0.6056***	-0.6466***	-0.6182***	-0.6528***	-0.6394***
North Center	-0.4639***	-0.5371***	-0.4864***	-0.5063***	-0.4943***
West Town	-0.7009***	-0.7510***	-0.7163***	-0.7632***	-0.7455***
Ward 1	0.1289	0.1050	0.1215	0.1082	0.1141
Ward 26	-0.2263**	-0.2812**	-0.2432*	-0.2536**	-0.2459*
Ward 27	0.0348	0.1905	0.0828	0.0499	0.0456
Ward 32	0.1937***	0.1841**	0.1908***	0.1747**	0.1801***
Ward 35	-0.5436***	-0.6072***	-0.5632*	-0.5491***	-0.5475
Ward 43	0.2965**	0.3157**	0.3024***	0.2549**	0.2668**
Ward 44	0.2542***	0.2674***	0.2583***	0.2333**	0.2393***
1996	0.1184	0.1700	0.1343	0.1317	0.1279
1997	0.0734	0.1132	0.0857	0.0917	0.0865
1998	0.4220***	0.4735***	0.4378***	0.4327***	0.4296***
1999	0.6245***	0.6766***	0.6406***	0.6393***	0.6351***
2000	0.6993***	0.7588***	0.7176***	0.7164***	0.7116***
2001	0.6650***	0.7002***	0.6758***	0.6659***	0.6656***
2002	0.8272***	0.8940***	0.8478***	0.8400***	0.8364***
2003	1.0012***	1.0486***	1.0158***	1.0092***	1.0069***
Constant	6.3912***	7.0645***	6.5985***	6.7019***	6.6136***
λ			0.3079		0.7158

Notes. The sample comprises 399 properties that sold within 2 years prior to the time a demolition permit was issued. The dependent variable is the natural log of sales price. Significance levels of 1%, 5%, and 10% are indicated by "***", "**", and "*".

Table 4
Regressions for Non-Teardown Properties

	Unrestricted		Restricted		Stein-Like Rule	
Variable	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Age in 1997	-0.0001	0.0002				
Basement	0.0439***	0.0088				
Basement is finished	0.0228**	0.0083				
Fireplace	0.0646***	0.0128				
Central air	0.1039***	0.0129				
Garage, 1-car	0.0032	0.0104				
Garage, 2 or more cars	0.0417***	0.0082				
Garage is attached	0.0650***	0.0169				
Multi-family	-0.1338***	0.0100				
Log of building area	0.3957***	0.0107				
Brick construction	0.0888***	0.0080				
Distance from EL stop	-0.4121***	0.0162	-0.4980***	0.0179	-0.4125***	0.0166
Near Lake Michigan	0.0638*	0.0301	0.1479***	0.0336	0.0641*	0.0278
Near rail line	-0.0769***	0.0081	-0.0845***	0.0091	-0.0770***	0.0084
Log lot size	0.2975***	0.0126	0.3809***	0.0111	0.2979***	0.0181
Lakeview	-0.1218***	0.0221	-0.3015***	0.0243	-0.1226***	0.0252
Logan Square	-0.4638***	0.0210	-0.6698***	0.0227	-0.4647***	0.0239
North Center	-0.2722***	0.0209	-0.5141***	0.0226	-0.2733***	0.0234
West Town	-0.4420***	0.0226	-0.5710***	0.0246	-0.4425***	0.0257
Ward 1	0.0016	0.0198	-0.0303	0.0221	0.0015	0.0206
Ward 26	-0.1238***	0.0156	-0.1957***	0.0174	-0.1241***	0.0153
Ward 27	0.0949**	0.0290	0.0113	0.0324	0.0945**	0.0289
Ward 32	0.2236***	0.0122	0.2241***	0.0135	0.2236***	0.0105
Ward 35	-0.2687***	0.0162	-0.3047***	0.0181	-0.2689***	0.0146
Ward 43	0.2738***	0.0240	0.2636***	0.0265	0.2738***	0.0275
Ward 44	0.1697***	0.0182	0.2455***	0.0203	0.1700***	0.0154
1996	0.1048***	0.0144	0.1108***	0.0162	0.1048***	0.0134
1997	0.2217***	0.0141	0.2251***	0.0159	0.2217***	0.0133
1998	0.3592***	0.0142	0.3725***	0.0160	0.3593***	0.0135
1999	0.5202***	0.0142	0.5311***	0.0160	0.5203***	0.0136
2000	0.6682***	0.0152	0.6670***	0.0171	0.6682***	0.0141
2001	0.7481***	0.0148	0.7488***	0.0166	0.7481***	0.0151
2002	0.8248***	0.0146	0.8146***	0.0164	0.8248***	0.0142
2003	0.9048***	0.0143	0.8973***	0.0161	0.9048***	0.0162
Constant	7.1180***	0.1057	9.7270***	0.0917	7.1180***	0.1057
R^2	0.6993		0.7825		F(11,11029) = 271.85***	

Notes. The sample comprises 11064 properties that sold between 1995 and 2003. The dependent variable is the natural log of sales price. Significance levels of 1%, 5%, and 10% are indicated by "***", "**", and "*". For the Stein-like estimator, $\lambda = 0.0045$.

Table 5
Probit Model of Teardowns

Variable	Coefficient	Standard Error
Age in 1997	0.0056***	0.0016
Basement	-0.2667***	0.0350
Basement is finished	0.0655*	0.0349
Fireplace	-0.2675***	0.0641
Central air	-0.3389***	0.0599
Garage, 1-car	-0.0480	0.0434
Garage, 2 or more cars	-0.0722**	0.0339
Garage is attached	-0.1150	0.0914
Multi-family	0.1673***	0.0403
Brick construction	-0.2649***	0.0332
Distance from EL stop	-0.6310***	0.0782
Near Lake Michigan	0.2895**	0.1229
Near rail line	0.0294	0.0339
Log lot size	0.2441**	0.1080
Lakeview	-0.3443***	0.0898
Logan Square	-0.5988***	0.0904
North Center	-0.4670***	0.0872
West Town	-0.3301***	0.0949
Ward 1	0.3422***	0.0859
Ward 26	-0.1025	0.0741
Ward 27	0.3293***	0.1254
Ward 32	0.5092***	0.0533
Ward 35	-0.6178***	0.0891
Ward 43	0.4582***	0.1012
Ward 44	0.6555***	0.0714
Log of floor area ratio	-0.9812***	0.0951
Land area divided by census tract average	-0.0495***	0.0134
Building area divided by census tract average	-0.0070	0.1007
Age divided by census tract average	0.3027**	0.1180
Constant	-3.5871***	0.7881
Average Likelihood	0.6899	
Pseudo R^2	0.1890	

Table 6
Selection-Bias Corrected Regressions for Teardown Properties

	Unrestricted		Restricted		Stein-Like Rule	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age in 1997	0.0018	0.0025				
Basement	0.0185	0.0754				
Basement is finished	0.0303	0.0386				
Fireplace	0.0488	0.0988				
Central air	0.0719	0.1133				
Garage, 1-car	-0.0540	0.0441				
Garage, 2 or more cars	-0.0409	0.0390				
Garage is attached	0.0426	0.0941				
Multi-family	-0.0259	0.0618				
Log of building area	0.0152	0.2676				
Brick construction	0.0758	0.0774				
Distance from EL stop	-0.4146**	0.1756	-0.4479***	0.0821	-0.4479***	0.1024
Near Lake Michigan	0.5353***	0.1826	0.6010***	0.1683	0.6010***	0.2019
Near rail line	0.0054	0.0340	0.0055	0.0332	0.0055	0.0331
Log lot size	0.7597**	0.3161	0.7774***	0.0691	0.7774***	0.1668
Lakeview	-0.3392**	0.1367	-0.3676***	0.0807	-0.3676***	0.0787
Logan Square	-0.7099***	0.1977	-0.7117***	0.0826	-0.7117***	0.1139
North Center	-0.5471***	0.1626	-0.5799***	0.0775	-0.5799***	0.0929
West Town	-0.7604***	0.1344	-0.7568***	0.0845	-0.7568***	0.1126
Ward 1	0.1747	0.1128	0.1749**	0.0822	0.1749*	0.1063
Ward 26	-0.2497***	0.0879	-0.2815***	0.0775	-0.2815***	0.1122
Ward 27	0.0826	0.1785	0.1489	0.1548	0.1489	0.1465
Ward 32	0.2694*	0.1405	0.2853***	0.0576	0.2853***	0.0760
Ward 35	-0.6454***	0.2155	-0.7055***	0.1247	-0.7055***	0.2378
Ward 43	0.3592**	0.1433	0.3918***	0.0955	0.3918***	0.0957
Ward 44	0.3537*	0.1835	0.3687***	0.0722	0.3687***	0.0981
1996	0.1258	0.1007	0.1362	0.1003	0.1362	0.1072
1997	0.0812	0.0961	0.0953	0.0952	0.0953	0.0979
1998	0.4300***	0.0944	0.4316***	0.0940	0.4316***	0.1059
1999	0.6316***	0.0922	0.6367***	0.0916	0.6367***	0.0964
2000	0.7095***	0.0948	0.7142***	0.0941	0.7142***	0.1062
2001	0.6722***	0.0972	0.6729***	0.0969	0.6729***	0.1205
2002	0.8349***	0.0976	0.8452***	0.0968	0.8452***	0.1054
2003	1.0077***	0.0948	1.0187***	0.0945	1.0187***	0.1049
Constant	5.7526***	1.2551	5.8655***	0.5988	5.8655***	0.9359
Selection-bias variable	0.2117	0.3596	0.2654***	0.0442	0.2654	0.1783

Notes. The sample comprises 399 properties that sold within 2 years prior to the time a demolition permit was issued. The dependent variable is the natural log of sales price. Significance levels of 1%, 5%, and 10% are indicated by "***", "**", and "*". For the Stein-like estimator, $\mu = 11.0797$ and $1 - a/\mu = 0$.

Table 7
Selection-Bias Corrected Regressions for Non-Teardown Properties

Variable	Unrestricted Coef.	Unrestricted Std. Err.	Restricted Coef.	Restricted Std. Err.	Stein-Like Rule Coef.	Stein-Like Rule Std. Err.
Age in 1997	-0.0005	0.0003				
Basement	0.0659***	0.0122				
Basement is finished	0.0176	0.0113				
Fireplace	0.0857***	0.0198				
Central air	0.1299***	0.0192				
Garage, 1-car	0.0071	0.0141				
Garage, 2 or more cars	0.0460***	0.0110				
Garage is attached	0.0601**	0.0275				
Multi-family	-0.1443***	0.0134				
Log of building area	0.4676***	0.0207				
Brick construction	0.1101***	0.0113				
Distance from EL stop	-0.3684***	0.0249	-0.5854***	0.0343	-0.3730***	0.0189
Near Lake Michigan	0.0472	0.0401	0.1428***	0.0473	0.0504***	0.0308
Near rail line	-0.0824***	0.0110	-0.0632***	0.0143	-0.0822***	0.0087
Log lot size	0.2274***	0.0232	0.5687***	0.0458	0.2343***	0.0190
Lakeview	-0.0866***	0.0294	-0.2928***	0.0414	-0.0918***	0.0263
Logan Square	-0.4020***	0.0303	-0.7325***	0.0470	-0.4097***	0.0266
North Center	-0.2212***	0.0288	-0.5228***	0.0415	-0.2288***	0.0263
West Town	-0.4014***	0.0310	-0.6213***	0.0466	-0.4070***	0.0265
Ward 1	-0.0277	0.0275	0.0960***	0.0347	-0.0260	0.0208
Ward 26	-0.1182***	0.0226	-0.1573***	0.0324	-0.1189***	0.0153
Ward 27	0.0668*	0.0398	0.1722***	0.0500	0.0693***	0.0307
Ward 32	0.1815***	0.0181	0.3630***	0.0224	0.1843***	0.0129
Ward 35	-0.2407***	0.0268	-0.3643***	0.0474	-0.2431***	0.0155
Ward 43	0.2499***	0.0327	0.3532***	0.0465	0.2500***	0.0276
Ward 44	0.1181***	0.0252	0.3598***	0.0269	0.1216***	0.0189
1996	0.1060***	0.0144	0.1017***	0.0149	0.1053***	0.0137
1997	0.2215***	0.0140	0.2204***	0.0146	0.2212***	0.0133
1998	0.3581***	0.0141	0.3637***	0.0150	0.3582***	0.0136
1999	0.5193***	0.0142	0.5238***	0.0149	0.5191***	0.0140
2000	0.6673***	0.0152	0.6692***	0.0163	0.6670***	0.0145
2001	0.7480***	0.0147	0.7467***	0.0155	0.7476***	0.0142
2002	0.8238***	0.0145	0.8236***	0.0149	0.8233***	0.0142
2003	0.9048***	0.0142	0.9004***	0.0147	0.9045***	0.0158
Constant	7.0286***	0.1724	8.4181***	0.3971	7.0581***	0.1350
Selection-bias variable	0.2542***	0.0408	-0.7908***	0.0503	0.2378***	0.0471

Notes. The sample comprises 11064 properties that sold between 1995 and 2003. The dependent variable is the natural log of sales price. Significance levels of 1%, 5%, and 10% are indicated by "***", "**", and "*". For the Stein-like estimator, $\mu = 664.1361$ and $1 - a/\mu = 0.9729$