How Tax Credits Have Affected the Rehabilitation of the Boston Office Market

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Abstract This paper is concerned with the extent to which rehabilitation tax credits affect the conditional probability of commercial real estate rehabilitation. The analysis suggests that rehabilitation tax credits have been a significant determinant of the conditional probability of rehabilitation in the Boston office market. A significant portion of rehabilitation tax credit investment is investment that would have been invested elsewhere, about 60% to 65% in certain periods, but rising to as high as 90% in other periods. The findings indicate that the rehabilitation tax credit has a significant and substantial influence on the conditional probability of rehabilitation. The findings also reveal that the greatest amount of slippage, not too surprisingly, generally occurs when the tax credit is low and when the gain from rehabilitation before the tax credit is high.

Relatively little has been written about the rehabilitation tax credit, even though it has been a feature of the tax code in the United States 1978. After the Tax Reform Act of 1986 (TRA 86), the rehabilitation tax credit was applied to industrial, commercial, and other income-producing buildings (factories, retail stores, hotels, and motels) built and originally placed in service before 1936.[1] The amount of the rehabilitation tax credit varies with the age and use of the structure. The credit is allowed for all recognized expenditures provided the expenses are substantial. The primary motivation for the rehabilitation tax credit is to favor the rehabilitation of older, more centrally located buildings that are already served by an existing infrastructure of streets, utilities, and civic buildings as against the construction of new buildings at the urban fringe.

This research uses data from a panel survey of the Boston office market to examine the effectiveness of the rehabilitation tax credit. Past analyses directed at ascertaining the effectiveness of tax credits have produced mixed results.[2] Clark (1979) and Hendershott and Hu (1981), for example, use time series observations of equipment investment and the cost of capital to uncover the relationship between tax credits and the level of investment. Their results show only modest effects of investment subsidies. Auerbach and Hassett (1991) use an event-study methodology to examine the effectiveness of investment subsidies. Their findings suggest no statistical relationship between investment spending and changes in the investment tax credit. Cummins, Hassett, and Hubbard (1994), on the other hand, using cross-sectional responses to tax law changes to identify exogenous shocks to firms' investment conditions, find that tax policy has a significant and large effect on investment.

The techniques used in this paper are inspired by the literature on failure time models (e.g., Cox, 1972; and Kalbfleisch and Prentice, 1980). The empirical model relates the conditional probability of rehabilitation to the value of the rehabilitation tax credit and other characteristics. The model is used to forecast the rate of rehabilitation with and without the rehabilitation tax credit. This empirical approach has several advantages. First, it makes possible a much clearer comparison of the relative effects of different factors on the decision to rehabilitate. Second, it permits the use of right-censored data (unrehabilitated properties). And third, it avoids certain econometric problems—aggregation and simultaneity bias—that plague the past literature.[3]

The paper proceeds as follows. First, a simple model of the rehabilitation decision for the conditional probability of rehabilitation is presented, which can be derived as a function of the gain from renovation, including the rehabilitation tax credit. The greater the gain from renovation before the rehabilitation tax credit, the greater the conditional probability of rehabilitation, all else held equal. In addition, tax credits can have a significant effect on the conditional probability of rehabilitation. After a brief discussion of the empirical methodology, the endogenous variables used in the model, and the data series to be used in this paper, a failure time model of the conditional probability of rehabilitation is estimated. As will become clear, there is a formal similarity between failure time models and the empirical work of Clark (1979) and Hendershott and Hu (1981). This occurs because of the negative slope of the marginal revenue curve. As the marginal cost curve shifts downward with a higher level of tax credit, the equilibrium level of rehabilitation must therefore increase for each structure previously and currently feasible for rehabilitation. Any structures newly feasible for rehabilitation would of course simply add additional expenditures, resulting in a monotonic relationship between the probability of rehabilitation and the level of rehabilitation expenditures.

The model is used to forecast the number of eligible buildings that would have been rehabilitated in the absence of the tax credit. To measure the degree of slippage associated with the rehabilitation tax credit, the fraction of eligible buildings that would have been rehabilitated even without the tax credit is computed. An ernest attempt is made to control for the net (before tax) financial incentives to rehabilitate a building before attempting to determine whether changes in the rehabilitation tax credit explain changes in rehabilitation activity.

The findings clearly suggest that rehabilitation tax credits are a significant determinant of both the conditional and unconditional probabilities of rehabilitation. The findings also suggest that a significant portion of rehabilitation tax-credit investment spending is spending that would have been invested otherwise, about 60% to 65% in certain periods, but rising to as high as 90% in other periods. The greatest amount of slippage, not too surprisingly, generally occurs when the tax credit is low and when the gain from rehabilitation before the tax credit is high.

Theory

Assume that the office market consists of n identical properties with an age distribution of $f(a)$ and ages $(a_0(= 0), a_1, a_2, \ldots, a_n)$ in period $t = 0$. Owners at any period $t \geq 0$ must decide whether or not to rehabilitate their structures and the extent of rehabilitation. The decision to rehabilitate occurs when the marginal revenue, MR, from rehabilitation is expected to be greater than the marginal cost, MC. Here, marginal revenue consists of the expected increase in rental revenues plus the increased sales price at reversion, discounted at the appropriate discount rate. Marginal costs include the costs of rehabilitation incurred in period t, less any reduction in operating costs over time, plus any increment (or less any decrement) in costs associated with sale at reversion, again discounted at the appropriate discount rate.

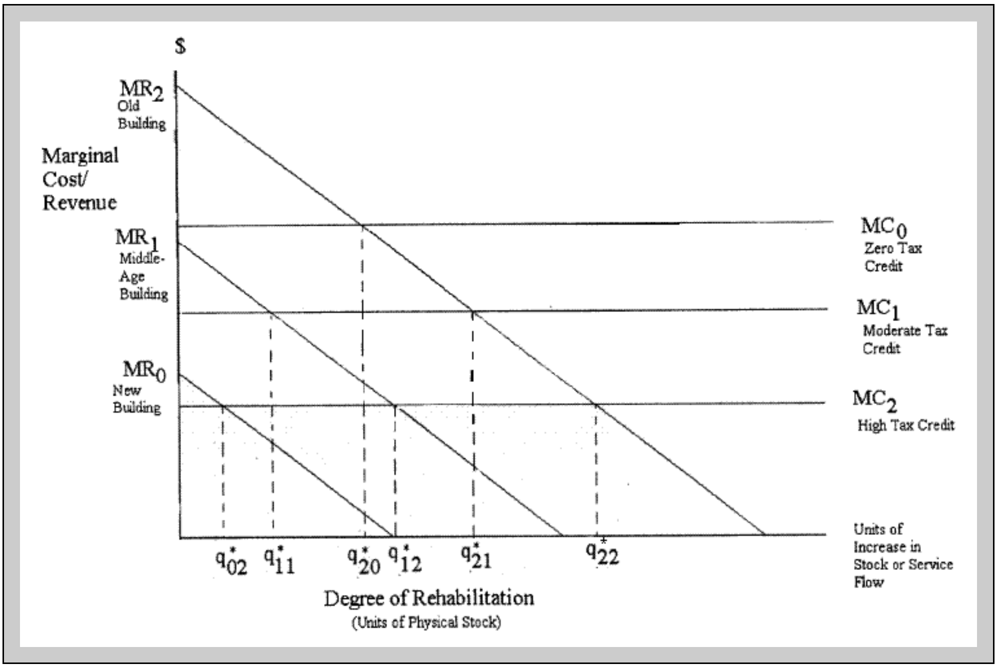
Also included in the marginal cost is the value of the rehabilitation timing option. This option value is equal to the opportunity cost of investing now instead of waiting. Define MC' as the marginal cost of investing now (excluding the value of the option to postpone rehabilitation). Define V as the value of the rehabilitation timing option. As is well established in the real options literature (see Titman, 1985; Childs, Riddiough, and Triantis, 1996; Trigeorgis, 1996; Williams, 1997; and Moore, 2001), V depends on the risk-free rate and the volatility in rents. As the risk-free rate increases, V increases because the expenditure is delayed and interest is earned. Similarly, the option to invest provides insurance against declines in the value of the project, and so as the volatility in rents increases, deferring investment is more valuable. Furthermore, because the volatility in rents is likely to be a function of structure age, V should increase with structure age, assuming the volatility of rents does so.

Further, assume that a tax credit at rate α_h is allowed on rehabilitation expenditures. For convenience, also assume the marginal cost of rehabilitation is invariant with respect to the degree of rehabilitation for structures of all vintages over the range of analysis. The baseline marginal cost in the absence of a tax credit is given by $MC_0 = MC' + V$, MC_1 and MC_2 then represent the marginal cost of rehabilitation when more generous rehabilitation tax credits are allowed. More specifically, MC_1 is defined by $MC_1 = (1 - \alpha_1)MC' + V$ and MC_2 is defined by $MC_2 = (1 - \alpha_2)\, MC' + V$, where $\alpha_2 > \alpha_1$.

Now consider the marginal revenue from rehabilitation. Marginal revenue should vary significantly for structures of different vintages. This is depicted in Exhibit 1 for three different structures: new, middle-aged, and older structures, where the vertical axis represents the marginal cost or revenue from rehabilitation and the horizontal axis represents the degree of rehabilitation in units of physical stock or services per unit time. In Exhibit 1, any age a_i greater than a_0 yields a higher MR_i. Notice that, because the marginal revenue curve MR_0 for newly built structures is below the marginal cost curve except for the extreme case of MC_2, owners will not rehabilitate new structures under any but the most extreme tax credit scenarios. It is also important to note that, even in the case of an extremely high tax credit, the equilibrium level of rehabilitation for a new structure, q^*_{02}, is quite low.

For mid-life structures, the marginal revenue curve is given by MR_1. Here again, the value of MR_1 is such that no mid-life structure would be rehabilitated under a tax scenario of zero tax credit. However, under a moderate tax credit regime represented by the marginal cost curve MC_1, rehabilitation would take place up to the point q^*_{11}. It can also be seen that a deeper tax credit results in a higher equilibrium level of rehabilitation (i.e., at q^*_{12} rather than q^*_{11}). With regard to older structures, the curve in Exhibit 1 labeled MR_2 shows that, in the absence of a tax credit, it is profitable to rehabilitate older structures up to the level q^*_{20}. Note that the result of increasing the tax credit in this case is simply to raise the

Exhibit 1 | Optimal Rehabilitation Under Alternative Tax Credit Regimes

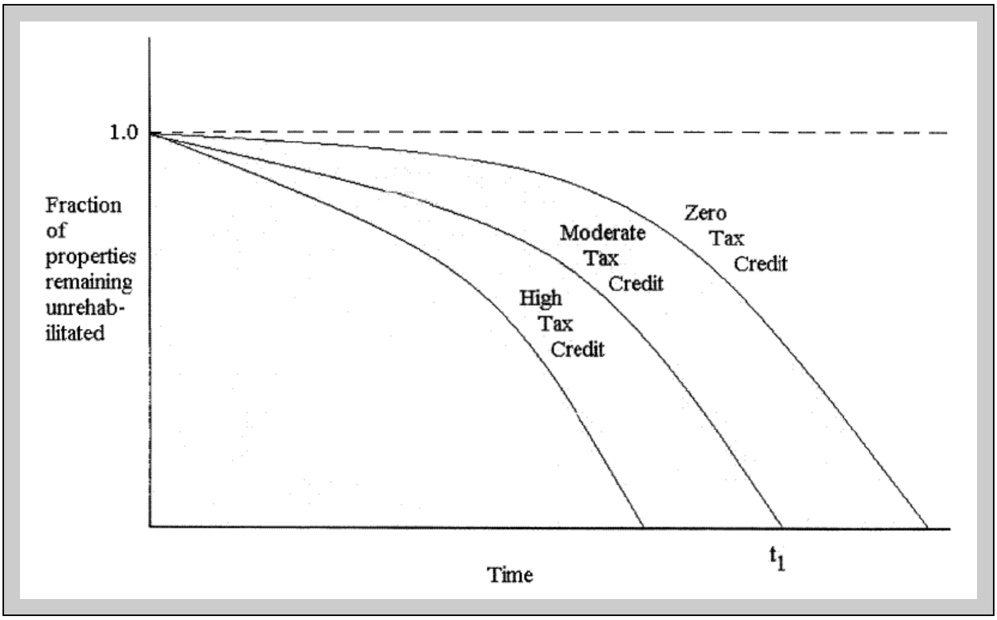


level of rehabilitation expenditures. With a moderate rehabilitation tax credit, for example, rehabilitation will occur up to the point q^*_{21}. Meanwhile, the presence of an extreme tax credit serves to increase the equilibrium level of rehabilitation to q^*_{22}.

This analysis clearly shows that the degree of investment and slippage is dependent on both the depth of the tax credit and the distribution of structure ages. In the simple case where there are just the three structures shown in Exhibit 1, and where there is a moderate tax credit on all rehabilitation expenditures, the proportion of rehabilitation tax-credit investment spending (in physical units) that is spending that would have been invested otherwise (or slippage) is $q^*_{20}/(q^*_{21} + q^*_{11})$. In the high tax credit case, the degree of slippage is $q^*_{20}/(q^*_{22} + q^*_{12} + q^*_{02})$. Since $q^*_{20}/(q^*_{22} + q^*_{12} + q^*_{02}) < q^*_{20}/(q^*_{21} + q^*_{11})$, or equivalently $q^*_{22} + q^*_{12} + q^*_{02} > q^*_{21} + q^*_{11}$, it is suggested that rehabilitation tax-credit-induced investment spending increases as the rehabilitation tax credit increases, all else held constant. Obviously, a higher proportion of buildings rendered feasible for rehabilitation results in greater incremental private investment, hence a lower degree of slippage, *ceteris paribus*.[4]

Now consider Exhibit 2, which represents the percentage "survival" of unrehabilitated buildings as a function of time t since the implementation of the historic rehabilitation tax credit. At each period, building owners go through the above rehabilitation calculus, given their building's age, current market conditions, their expectations about the future, and the current tax credit rule. A certain

Exhibit 2 | Aggregate Survival Curves Under Alternative Tax Credit Regimes



proportion $\lambda(t)$ of the original universe of owners decides to rehabilitate, leaving behind $S(t) = 1 - \lambda(t)$ unrehabilitated structures (i.e., the "survivors"). In period $t + 1$, the remaining population of buildings has aged one period. The marginal revenue curves shift accordingly, perhaps bringing additional structures into the range of feasibility for rehabilitation. Over time, a cohort survival curve is generated that is unique to each tax credit regime.[5] Note that the "no credit" regime would be expected to result in the highest rate of survivability of non-rehabilitated structures and vice versa for the high-credit regime. Note also that the vertical and horizontal differences between the survival curves graphed in Exhibit 2 depend on the distribution of buildings across vintages. This implies that the pattern of rehabilitation observed over time under a given tax credit regime will be dependent on the vintage distribution.

Econometric Methodology

The goal of the empirical analysis is to examine the effects of tax credits on the rehabilitation of the Boston office market. In the spirit of the notion of survivorship developed in the last section, the methodology employed follows that of Cox (1972). The Cox hazard model determines both the conditional probability of rehabilitation at time period t that would be appropriate under neutral economic conditions (which is commonly referred to as the "baseline hazard rate"), $\lambda(t)$ and the conditional probability of rehabilitation relative to this baseline as tax policy and economic conditions change. The model builds in the assumption that if a variable increases the likelihood of rehabilitation, it also decreases the time to rehabilitation.

A Weibull distributional form is used for the hazard function, which allows for any monotonic effect. The baseline hazard is given by the following:

$$\lambda(t) = \gamma p \, (\gamma t)^{p-1} \tag{1}$$

and the hazard function relative to this baseline hazard rate is:

$$\lambda(xt; t) = \lambda(t) \, exp(\beta_{1x1t} + \beta_{1x1t} + \ldots + \beta_{1x1t} + \theta_{zt}) \tag{2}$$

where:

z_t = The gain from rehabilitation before the rehabilitation tax credit;
x_t = $(x_{1t}, x_{2t}, \ldots, x_{nt})$ is a vector of contemporaneous characteristics of the property and the market (including tax policy);
γ and p = Parameters of the Weibull distribution;

$\beta = (\beta_1, \beta_2, \ldots, \beta_n)$ indicates the direction and magnitude of the effect of $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$ on the conditional probability of rehabilitation; and
$\theta =$ The coefficient of the gain from rehabilitation variable.

The baseline hazard rate in Equation (1) is a simple generalization of the exponential distribution. For $p < 1$, the baseline hazard rate is monotone decreasing with respect to time; for $p > 1$, the baseline hazard rate is increasing with respect to time; and for $p = 1$, the baseline hazard rate remains constant as time increases. The latter is the exponential case.[6]

Several comments about $\lambda(t)$, $\lambda(t; x_t)$, and $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$ are worthy of attention. First, both $\lambda(t)$ and $\lambda(t; x_t)$ are conditional probabilities [i.e., $\lambda(t)$ and $\lambda(t; x_t)$ refer to the probability of rehabilitating a property in period t given that the property has not been previously rehabilitated]. Second, the baseline hazard rate, $\lambda(t)$, is the probability that rehabilitation will take place under completely stationary, homogeneous conditions. The Weibull distribution is used because it is generally expected that the office building rehabilitation time distribution will be monotonic (see below). Other distributions, such as the lognormal or log-logistic distribution, assume that the hazard function should first increase and then decrease.[7] Third, the covariates in Equation (2) act multiplicatively on the baseline rate. Fourth, values of $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$ are allowed to vary over time. This means that the integrated hazard, survivor, and density functions will, in general, depend on the entire time path (up to t) of the regressor and that the estimation of $\beta = (\beta_1, \beta_2, \ldots, \beta_n)$ will require numerical maximization of the log-likelihood function.

Let R_{rt} and R_{ut} be the rehabilitated and unrehabilitated property rents for building i at time t and let ρ_t be the cost of renovation (measured as a percentage of original value). Building i will otherwise be rehabilitated (ignoring the effects of the rehabilitation tax credit) if:

$$z_t = \log(R_{rt}/R_{ut}) \geq \rho_t. \tag{3}$$

i.e., building i will be rehabilitated if z_t, the percentage property rent differential, exceeds the cost of renovation.

New properties are expected to possess relatively little economic incentive for rehabilitation (i.e., z_t should be close to zero or possibly negative, and $z_t - \rho_t < 0$). *Ceteris paribus,* z_t would then be expected to be monotonically related to age of the structure, starting off low for "young" buildings and gradually increasing to within a feasible range for "middle-aged" buildings that are ripe for rehabilitation. Older buildings that have been rehabilitated are assigned a new "effective age," defined as the time since rehabilitation, and z_t is reset to a lower level consistent with newer buildings. Those older buildings that have somehow escaped rehabilitation (consistent with the notion of market inefficiencies) would experience continuously higher (“supernormal”) levels of z_t.

A difficulty in estimating z_t is that while the actual property rent for each building is observed in the sample, the would-be rent on the building had rehabilitation occurred or not occurred (as the case may be) is unknown. As a result, z_t is unobservable. To estimate z_t, two hedonic rent equations are specified: one rent equation for rehabilitated properties and one for unrehabilitated properties. These are:

$$\log R_{ri} = y_i B_r + \varepsilon_i \tag{4}$$

$$\log R_{ui} = y_i B_u + \xi_i \tag{5}$$

where y_i is a vector of amenities and other characteristics explaining the determination of rental rates, B_r and B_u are coefficient vectors, and ε_i and ξ_i are normal error terms. Market asking rents per square foot are the dependent variables in Equations (4) and (5). The explanatory variables include building size, number of floors, property vacancy rate,[8] building age, and locational submarket.

For each rehabilitated property, the value of z_t is then set equal to the logarithm of the ratio of actual to predicted unrehabilitated rents, where the latter is obtained by inserting the amenity and other characteristics for each building into Equation (5). For each unrehabilitated property, the value of z_t is set equal to the logarithm of the ratio of predicted to actual unrehabilitated rents, where the former is obtained from Equation (4). The resulting value of z_t generally tends to be quite small for newer unrehabilitated buildings, since the observed value of R_{ui} tends to be relatively large in comparison to the estimated R_{ri}. As expected, properties that display the highest levels of z_t are middle-aged or older properties that have not yet undergone rehabilitation.

Prior to the estimation of Equation (2), the data are standardized by redefining the time to rehabilitation as the year of rehabilitation minus 1978, which is the base year. The age of the structure in 1978 is controlled by one of the regressors on the right-hand side of Equation (2).[9] All properties at the end of 1991 that were not yet rehabilitated were treated as censored observations. This is essentially the approach in the literature on unemployment duration and is an advantage of the Cox model, permitting proper evaluation of the rehabilitation tax credit hypothesis without assigning an arbitrary date for rehabilitation or assuming rehabilitation never occurs.

The model in Equation (2) can be rewritten as:

$$\log T = \alpha + xb + z\pi + \sigma(W + \nu), \tag{6}$$

where T is the year of rehabilitation minus 1978, $\alpha = -\ln \gamma$, $\sigma = (1/p)$, $b = (b_1, b_2, \ldots, b_n)$, $b_i = \sigma\beta_i$, $\pi = \sigma\theta$, $W = \ln[-\ln S(T)]$, ν is an additional error component added to the model because z happens to be a generated regressor, and $S(T)$ is the conditional survivor function for the ith property.

Estimation of Equation (6) poses two potentially vexing problems. First, with the inclusion of z on the RHS of Equation (6), which is estimated and not observed, the Weibull proportional hazards model has unobserved heterogeneity. Consequently, Equation (6) cannot be estimated by parametric maximum likelihood unless enough is known about the distribution of ν to specify the distribution of $W + \nu$ up to finitely many parameters. Correcting for this problem is not trivial and involves many tradeoffs. Heckman and Singer (1984a, 1984b) present a nonparametric maximum likelihood method that does not require knowledge of the distribution of ν. Their method produces consistent estimates, but nothing is known about the rate of convergence or asymptotic distribution, so it cannot be used for statistical inference. Additionally, the Heckman-Singer methodology is quite difficult to compute. Gourieroux, Monfort, and Trognon (1984a, 1984b) provide necessary and sufficient conditions for consistency and apply their methodology to basic Poisson models. However, to extend their technique to the Weibull model at hand would be a separate paper itself. Another approach (and the one employ employed in this research) is the use of an instrument such as *AGE* to proxy for z. The validity of this approach depends, of course, on the degree of appropriateness of the proxy. The performance of z in the estimated hazards models will be evaluated, along with its relationship to various proxies, such as *AGE*, before making a judgment about the best way to handle this quasi-maximum likelihood estimation issue.

The second potential problem with estimating Equation (6) is that the standard errors of b and π need to be adjusted to take into account the random sampling error in the estimators of B_r and B_u, but this is not difficult. This issue is resolved using the procedure outlined in Murphy and Topel (1985).

The Explanatory Variables

Following are the $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$ variables that were selected for inclusion in Equation (6):

1. **Rehabilitation Tax Credit (φ).** Each structure was evaluated as to the level of tax credit it would be eligible for as of its date of rehabilitation (or the end of the sample period for unrehabilitated structures). If the structure was not eligible for a credit, "zero" was entered. The rehabilitation tax credit variable is taken directly from the IRS code during the 1978–1991 observation period. It takes on one of five values: 10% in 1978–1980 for structures at least 20 years old; either 15% or 20% in 1981–1985 depending on whether the structure is at least 30 to 40 years old; 10% after 1985 for all properties that were built and originally placed in service before 1936; and 20% for certified historic structures.

2. **Age of the Structure in 1978 (*AGE*).** *AGE* is a correlate of the potential gain from rehabilitation and the marginal cost of rehabilitation. It also acts in a variety of other ways to potentially affect the rate of rehabilitation activity, both directly and indirectly. For example, *AGE* could be a proxy for unobserved quality differences or historic architectural characteristics. Of course, the correlation of *AGE* with other explanatory variables such as z can result in problems associated with multicollinearity.
3. **Building Size (*SQFT*).** Net rentable area of the building measured in square feet. This variable and its square are also used as a proxy for the cost of rehabilitation. There are expected to be economies of scale up to a point (shortening the time to rehabilitation) and diseconomies beyond that point.
4. **Building Height (*FLR*).** Number of floors. This variable also serves as a proxy for the cost of rehabilitation.
5. **Locational Submarket (*LOC*).** 0–1 location variables to control for ‘‘neighborhood’’ effects.
6. **Rental Volatility (*VOL*).** The standard deviation in metropolitan rent levels over the previous five years prior to the censor point or the time of rehabilitation was calculated and used as a simple proxy for volatility expectations.[10] Increased uncertainty in future rents in an option framework would be expected to make it advantageous to wait for additional information before deciding to rehabilitate.

The expected signs on these variables are worth noting. The rehabilitation tax credit variable should have a negative sign, since larger tax credits should provide a greater incentive to rehabilitate. This hypothesis is consistent with the model, in that rehabilitation tax credits are expected to push a project ‘‘over the top’’ and change it from a negative to a positive net present value project. The coefficient of *AGE* depends on the collinearity with z; if, say, *AGE* is a good instrument for z, then the coefficient on *AGE* should be positive. *AGE* could also increase the time to rehabilitation, for example, if *AGE* increases ρ_t. The coefficient on *SQFT* should be positive. Generally, the greater the building size, the higher the cost of rehabilitation. Additionally, a simultaneous rise in cost is likely to occur with higher elevations within a given structural class. Hence, *FLR* should have a positive coefficient.

The locational submarket variables are included as RHS variables in Equation (6) to control for neighborhood effects, the thought being that the decision to rehabilitate any one property depends in part on the district in which the property is located. Davis and Whinston (1966) recognize this issue with the notion that individually rational action may not allow for socially desirable investment in the redevelopment of properties in some neighborhoods (depending on the character of the neighborhood environment), but may allow it in other neighborhoods. This is tested below when $\lambda(t; x_t)$ is examined to see whether or not it is significantly different for different neighborhoods.

Finally, the coefficient on *VOL* should be positive; greater uncertainty in future rents should make it advantageous to wait for additional information before deciding to rehabilitate. There is evidence, however, of a strong positive correlation between *VOL* and the rehabilitation tax credit (φ).

Data

This study is based on a panel survey of the metropolitan Boston office market conducted by Spaulding & Slye Colliers. It covers a sample of 187 office buildings located in the City of Boston. The survey reports year built, year rehabilitated, asking rents, vacancy rate, building size, number of floors, and location for each building (sample statistics are summarized in Exhibit 3).[11] The earliest date of construction for any structure rehabilitated during the time period analyzed here was 1805, while the latest date was 1969. A substantial portion of the structures in the sample were built and originally placed in service in the late 1960s, 1970s, and 1980s.

The base year for the analysis is 1978 as it is the beginning year of the tax credit program. Each office building in the final sample is followed from 1978 through the end of 1991 or until the building is rehabilitated, whichever comes first. The effective "age" of an office building is considered the time since the last rehabilitation for those structures indicated to have been rehabilitated prior to

Exhibit 3 | Summary Statistics

	Mean	Std. Dev.	Min.	Max.
Time to rehab.[a]	9.29	4.27	0	14
Asking rent	$25.85	$6.74	$13.00	$50.00
Vacancy rate	0.17	0.20	11,010	1,589,000
Square feet	226,969	296,858	2	60
Floors	13	10	2	183
Building age (yrs)	59	42	0	1
North Station	0.10	0.30	0	1
Charlestown	0.06	0.24	0	1
Financial District	0.57	0.50	0	1
Fox Point Channel	0.06	0.24	0	1
South Station	0.03	0.17	0	1
Back Bay	0.18	0.39	0	1

Note:
[a] The base year is 1978.

1978. Several structures are indicated to have been rehabilitated more than once, but none during the sample period.

The number of properties rehabilitated between 1978 and 1991 are shown in Exhibit 4. The table is divided into two main parts. The first part shows the number of properties rehabilitated in the period 1978–1991 by year built (see columns 1–14). The second part of the exhibit shows the total number of rehabilitated properties by year built (column 15), as well as the number of buildings that were ‘‘censored,’’ that is existed as unrehabilitated structures at the end of the observation period in 1991 (column 16), the total number of properties built and originally placed in service during each decade (column 17), and finally the cumulative total number of properties in the sample that were built during each decade (column 18).[12] Of the 187 office buildings in the sample, 114 buildings were rehabilitated in the 1978–1991 period, while 73 were not. One hundred eleven of the 187 office buildings were eligible for rehabilitation tax credits during this time period. Of these properties, 108 buildings were rehabilitated in the 1978–1991 period, while three were not.

The Kaplan-Meier hazard function approach is used to measure the rate of rehabilitation.[13] The Kaplan-Meier hazard is the probability that a property will be rehabilitated at period *t*, conditional on the property’s reaching period *t* without prior rehabilitation. The natural estimator for this probability is the ratio of the number of properties rehabilitated at period *t* divided by the number of total properties ‘‘at risk’’ at period *t*. A plot of the Kaplan-Meier hazard is given in Exhibit 5. As a general rule, in any given year the hazard rates are essentially zero for buildings less than 20 years old. Thereafter, the sample rates have a distinct upward slope (particularly for buildings 50 years old or older). Obviously, in any mid-life or younger building, the additional value created by a rehabilitation program (either in terms of increased market value or increased income potential) tends to be quite small. This value generally grows over time as older buildings become outdated and physically deteriorated.

This data can also be viewed historically. This involves looking at the number of buildings rehabilitated each year, divided by the number of unrehabilitated buildings at the beginning of the year. These simple computations yield the results shown in Exhibit 6. As can be seen from the figure, the unconditional probability of rehabilitation in the Boston office market reaches a peak of about 15% in 1985, falls to 9% in 1987, and then rises to 16% in 1988. Then from 1988 to 1991, the probability declines from a peak of 16% to a low of 3%.

These data suggest a strong *a priori* possibility of a link between rehabilitation tax credits and rehabilitation activity, particularly over the 1981–1985 period, when a 15% tax credit was given to structures at least 30 years old and a 20% tax credit was given to structures at least 40 years old. Prior to that (i.e., from 1978 to 1981), nonresidential buildings at least 20 years old were only given a 10% rehabilitation tax credit. The data also suggest some reduction in rehabilitation activity in 1986 and subsequent years, coincident with a decline in the rehabilitation tax credit to 10% for all qualified structures built before 1936.

Exhibit 4 | Time to Rehabilitation for Sample Properties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Year Rehabilitated																	
Year Built	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	Total Rhb.	# Censored	# Built	Cum. Total
<1850	1				1						1				3	1	4	4
1850–1859								1				1			2		2	6
1860–1869							1	1	1			1	1	1	6		6	12
1870–1879		1		2	3		1	2		1			1		11		11	23
1880–1889							3		2		2				7		7	30
1890–1899			1		5		5	4	1	2	4	1	1		24		24	54
1900–1909		1	1	1	5		2	2	1	5	4		2	1	25	2	27	81
1910–1919				1	2	1	1	5	1	1		1			13	2	15	96
1920–1929		1	1	5			2	2	4		1	1			17		17	113
1930–1939															0		0	113
1940–1949											1		1		2		2	115
1950–1959							1								1		1	116
1960–1969								1			1	1			3	9	12	128
1970–1979															0	19	19	147
1980–1989															0	34	34	181
1990–1991															0	6	6	187
Total	1	3	3	9	16	1	16	18	10	9	14	6	6	2	114	73	187	

Notes: The table shows the number of office buildings in the Boston office market by year of construction and year rehabilitated. The sample period is from 1978 through 1991. These data were taken from a panel survey conducted by Spaulding & Slye Colliers.

Exhibit 5 | Plot of Kaplan- Meier Hazard Function

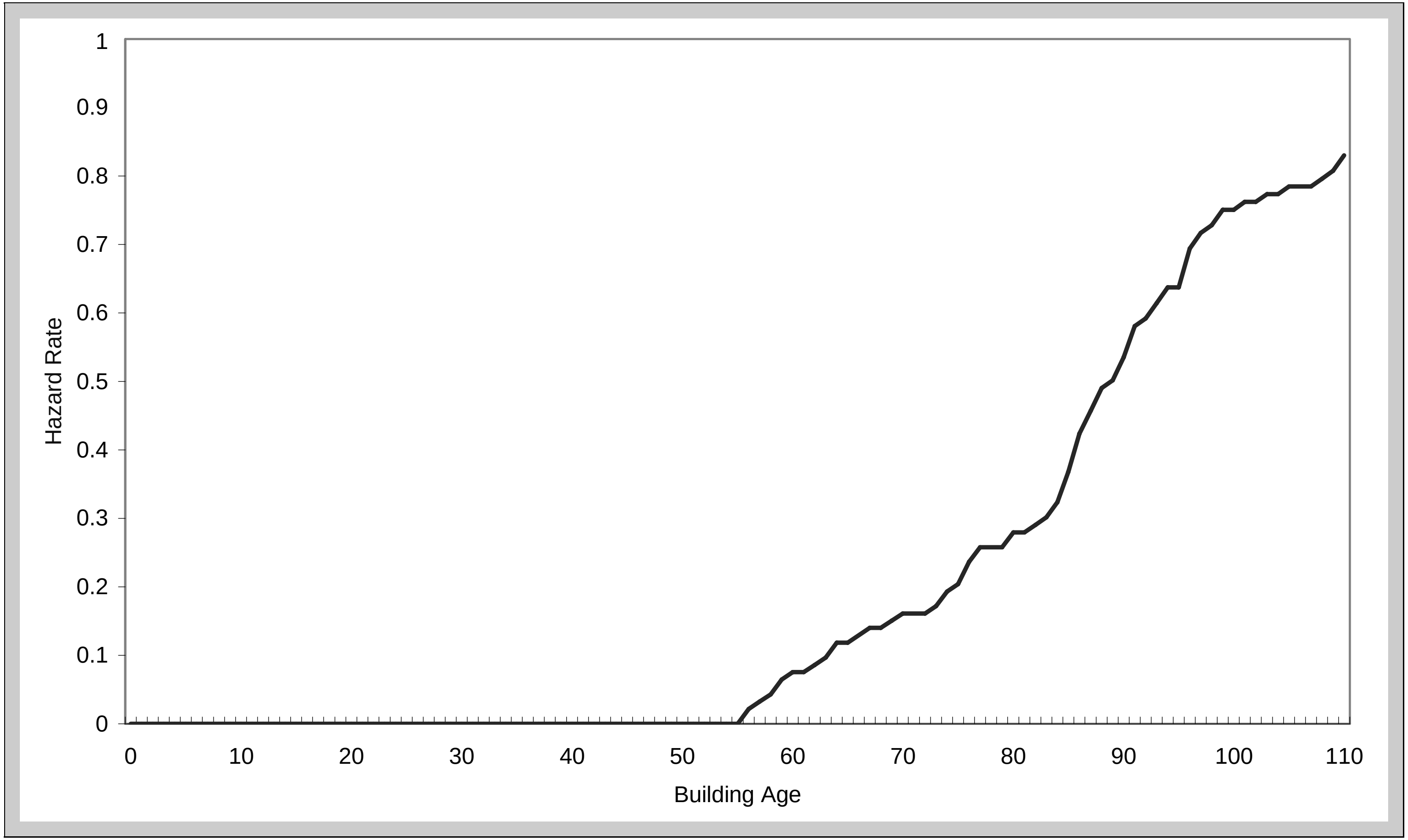
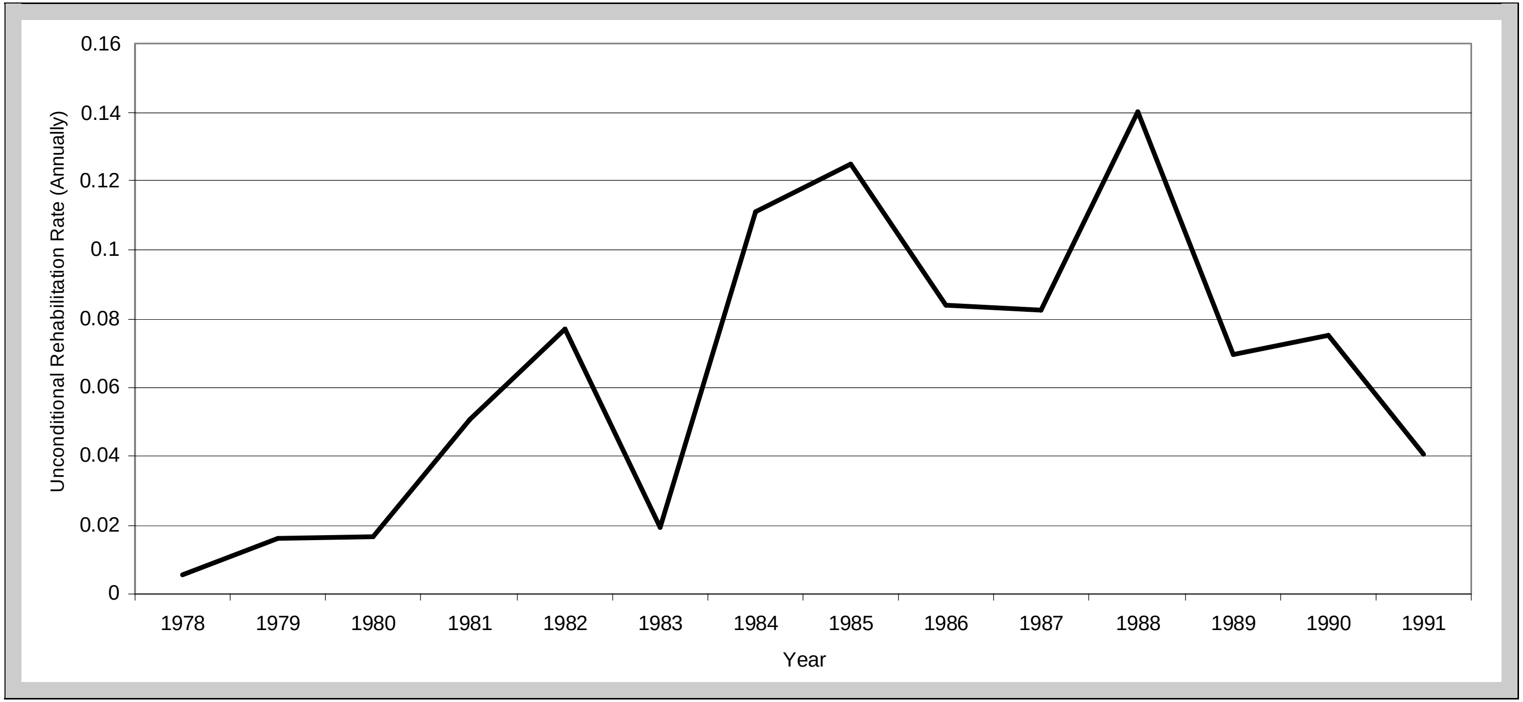


Exhibit 6 | Actual Rate of Rehabilitation by Year



The apparent positive correlation between the rehabilitation tax credit and rehabilitation activity is not conclusive evidence of a link between the two. A variety of other factors, including the significant increase in real estate tax depreciation benefits that was brought about by the Economic Recovery Tax Act (ERTA) of 1981 could account for some of the variation in rehabilitation activity.[14] In addition, the decline in rehabilitation activity in the Boston office market after 1985 coincides with the Tax Reform Act (TRA) of 1986, which significantly reduced the tax benefits from investing in office buildings. Finally, in addition to the changes in tax depreciation benefits over the study period, other covariates such as changes in after-tax required rates of return could easily explain the variation in rehabilitation activity over time.

Estimation Results: Gain from Rehabilitation

Estimates of Equations (4) and (5) are presented in Exhibit 7. The standard errors of the estimated coefficients are in parentheses. The asking rent data are from the Spaulding & Slye Colliers panel survey. Mean values of R_{rt} and R_{ut} are \$22.70 and \$29.65 per square foot, respectively. Overall, rents in the Boston office market were about \$25 per square foot per year in 1990–1991. This compares to an average market rent (in nominal dollars) of \$21 per square foot in 1976–1977, and about \$30 per square foot in 1988 (as reported by the National Real Estate Index). Between these two periods, average rents per square foot rose almost monotonically. Then after reaching a peak in 1987–1988, average rents per square foot fell precipitously.

All the other arguments in the rental hedonic equations were also obtained from the Spaulding & Slye Colliers panel survey. Interestingly, building vacancy rates in the Boston office market went from about 4.0% to 4.5% in 1980–1981 to over 19% in 1990–1991. By 1987, vacancy rates in the Boston office market were 13%. Yet new office construction continued to take place. There is some recent evidence to suggest that part of this investment activity was due to irrational and faddish behavior (e.g., Mei and Saunders, 1995). There also is evidence that some markets are prone to pronounced bursts of development activity following a fall in demand (as happened in the Boston office market during the mid to late-1980s), and that such behavior is entirely rational given the possibility of preemptive equilibria (see Grenadier, 1996).

The Spaulding & Slye Colliers survey identifies six distinct submarkets within the Boston office market. These include North Station, which is adjacent to the old Boston Garden; Charlestown, which is across the river and includes Old Cove, the site of Bunker Hill; the Financial District, which includes Quincy Market; Fort Port Channel, which is the old district of Boston; South Station, which includes the Federal Reserve Bank; and Back Bay, which includes Copely Square. Earlier work by Vandell and Lane (1989) on essentially the same data set as the current study finds a negative and significant relationship between distance to the city

Exhibit 7 | Rental Hedonic Estimations for Use in Estimating the Gain from Rehabilitation (*z*) for Rehabilitated and Unrehabilitated Buildings

Variable	Rehabilitated Buildings	Unrehabilitated Buildings
Intercept	3.194*** (0.156)	3.383*** (0.065)
SQFT	6.531E-8 (17.456E-8)	10.752E-8 (12.560E-8)
FLR	0.0053 (0.0067)	0.0053 (0.0037)
AGE	0.0002 (0.0008)	−0.0081*** (0.0016)
VACRATE	−0.0174 (0.1020)	0.1748 (0.1106)
LOGREHAB	−0.0537 (0.0453)	
North Station	−0.0881 (0.0724)	−0.2529** (0.0759)
Charlestown	−0.1023 (0.0780)	−0.4153 (0.1835)
Fox Point Channel	−0.2324** (0.0746)	−0.2711** (0.1309)
South Station	−0.1340 (0.0941)	−0.0049 (0.1785)
Back Bay	0.0330 (0.0508)	−0.0316 (0.0626)
Adj. R^2	0.107	0.559
F-Value	2.21**	9.16***
Dependent Mean	3.122 (log $22.70)	3.390 (log $29.65)

Notes: The dependent variable is log Rent. For rehabilitated buildings, $N = 101$; for unrehabilitated buildings, $N = 58$. Adjusted standard errors are in parentheses.
** Significant at the 10% level.
*** Significant at the 5% level.

center and asking rents in the Boston office market. The locational submarket indicator variables should pick up this effect.

The ordinary least squares rental hedonic results listed in Exhibit 7 explain 11% and 56% respectively of the cross-sectional variation in rents. Multicollinearity among several of the explanatory variables explains some of the insignificance of the coefficients (for example, size and number of floors). The *AGE* variable is highly significant in explaining rents for unrehabilitated buildings, with each year of age reducing rents by 0.8%. As expected, *AGE* is insignificant for rehabilitated buildings. Unrehabilitated buildings in the North Station and Fox Point Channel submarkets are found to experience significantly lower rents, about 25% lower, than those in the Financial District (the left-out category). This holds true also for rehabilitated buildings in the Fox Point Channel submarket, about 23% lower. Other submarket rents are insignificantly different from those of the Financial District, but the negative sign on most coefficients suggests that the Financial District tends to possess the highest rents in the market for both rehabilitated and unrehabilitated structures.

A variable indicating the log of the time (in years) since rehabilitation was included in the rehabilitated building hedonic model to control for subsequent adjustments in rent due to subsequent depreciation. The coefficient on this variable was negative, as expected, though insignificant. Although positive coefficients on the size of the building and number of floors variables were positive, as expected, they were insignificant.

The vacancy rate effect was not consistent or significant, although the expectation for this variable could vary depending on whether it is a proxy for a rent level diverging from equilibrium (in which case higher vacancies mean higher rents) or for unobserved quality differences (in which case higher vacancies mean lower quality, hence lower rents). If the explanatory variable values for *SQFT, FLR, VACRATE* are set, and the submarket indicators are set at the mean of the entire sample of buildings and ‘‘zero’’ is inserted for time since rehabilitation, a 40-year-old unrehabilitated building (*AGE* = 40) would rent for $22.45 per square, whereas if rehabilitated, it would rent for $29.40 per square foot, a 31% premium.

These rent estimates are used, along with the reported actual rental rates from the Spaulding & Slye Colliers panel survey, to determine the potential gain from rehabilitation before the tax credit for each building in the sample.[15] Exhibit 8 is a scatter diagram illustrating the relationship of these gain estimates and structure age for the sample of unrehabilitated and rehabilitated structures. As expected, the gain from rehabilitation generally rises from zero or negative levels for newer structures below about 25 years old (most of which were unrehabilitated) to as high as 50% to 100%, or even more, for older structures of 100 years of age or more. It appears that the critical age of a building to render rehabilitation feasible from an economic standpoint is between 25 and 50 years, consistent with the observed Kaplan-Meier hazard function results in Exhibit 5.

Estimation Results: Hazard Model

Exhibit 9 shows estimates of the proportional hazards model for the full sample (adjusted standard errors are presented in parentheses).[16] To evaluate the effects of multicollinearity, a simple model of time to rehabilitation is estimated as a function of the gain from rehabilitation without any other control variables. The rehabilitation tax credit, building size (and building size squared), height of the

Exhibit 8 | Estimated Gain from Rehabilitation by Age of Property

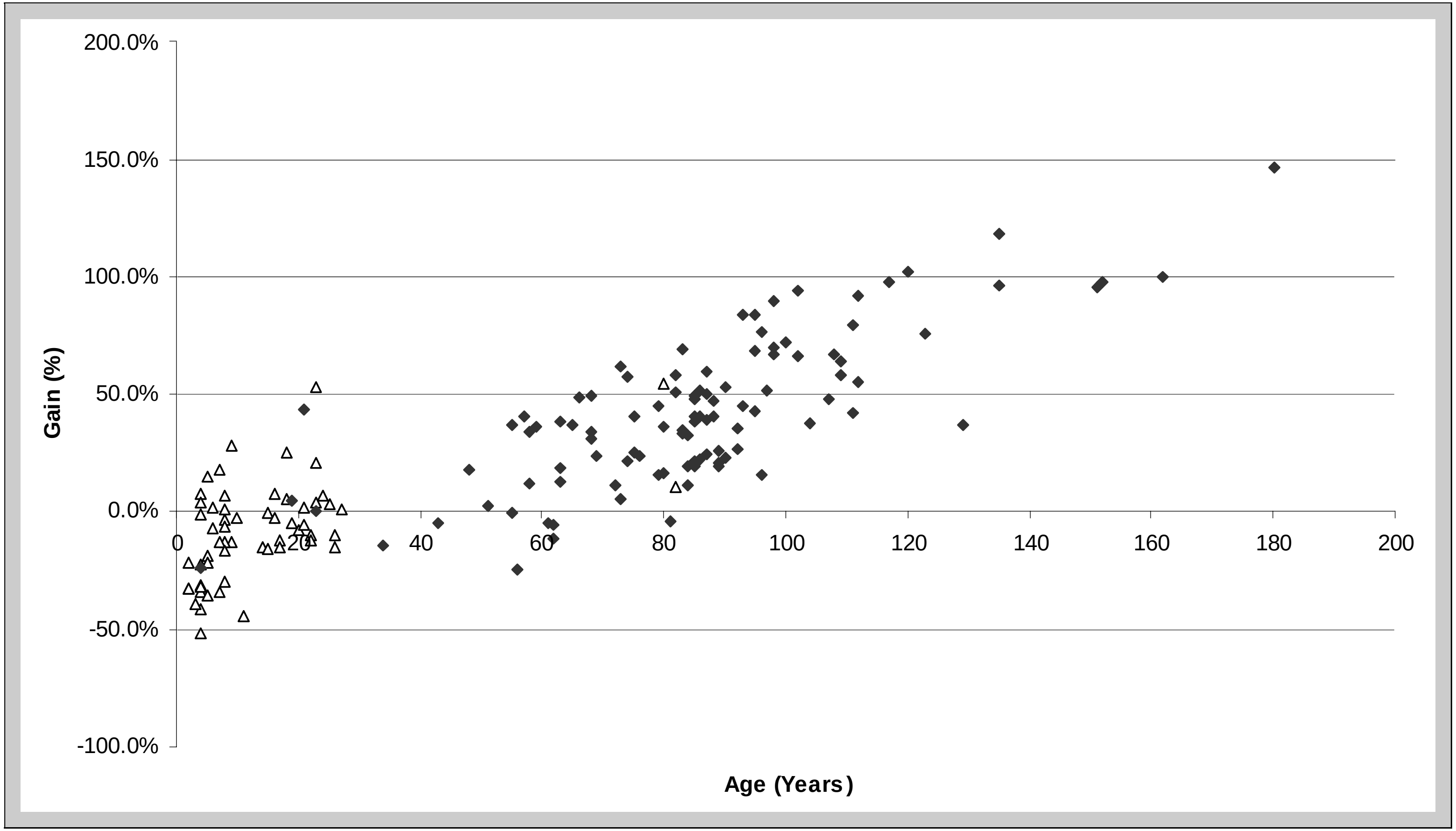


Exhibit 9 | Results of Estimating Proportional Hazards Mode (Weibull Distribution)

	Alternative Specification		
Variables	(1)	(2)	(3)
Intercept	2.82*** (0.11)	3.28*** (0.28)	3.36*** (0.26)
Gain from rehabilitation	−1.00*** (0.27)	0.23*** (0.20)	
Rehabilitation tax credit		−2.99** (1.67)	−2.97** (1.68)
SQFT		−1.84E-06** (1.06E-06)	−2.18E-06** (1.06E-06)
$SQFT^2$		1.77E-12 (1.41E-12)	2.23E-12 (1.43E-12)
FLR		0.03** (0.02)	0.02** (0.01)
Age of Building in 1978			
Greater than 50, but less than 75		−0.92** (0.31)	−0.86*** (0.31)
Greater than 75, but less than 100		−0.87*** (0.41)	−0.79*** (0.37)
Greater than 100		−1.08*** (0.18)	−0.96** (0.39)
North Station		0.08 (0.19)	0.08 (0.17)
Charlestown		0.27 (0.17)	0.33** (0.16)
Fox Point Channel		0.10 (0.17)	0.10 (0.17)
South Station		0.04 (0.27)	0.05 (0.22)
Back Bay		−0.03 (0.13)	−0.02 (0.12)
Scale	0.54 0.05	0.40 (0.03)	0.40 (0.03)
Log-likelihood	−149.8	−89.2	−89.9

Notes: The dependent variable is time to rehabilitation. For the whole sample, regression coefficients and adjusted standard errors (*N* = 187); there are 41 missing observations. Adjusted standard errors are in parentheses.

** Significant at the 10% level.

*** Significant at the 5% level.

building, age of the building in 1978, and five 0-1 location variables is added to the model in the second column. In the third column, gain from rehabilitation is dropped from the equation and the model is re-estimated with the other explanatory variables.

The results in column 1 of Exhibit 9 show that the gain from rehabilitation before the tax credit has the predicted negative sign. The coefficient of gain from rehabilitation is -1.00, and, with an adjusted standard error of 0.27, it is statistically different from zero at the 0.01 level of significance.

Adding *AGE* to the regression, however, significantly reduces explanatory power and the significance of the gain variable z. In column 2 of Exhibit 9, the t-Statistic for the coefficient of the gain variable changes from -3.70 to 1.15, which is attributable to the high positive correlation between gain from rehabilitation and building age (the correlation is 0.85).[17]

The rehabilitation tax credit variable, on the other hand, takes its predicted sign and is highly significant. The coefficient is -2.99 and is relatively tightly estimated. The coefficient of the rehabilitation tax credit suggests that an increase in the rehabilitation tax credit of 10 percentage points would lead to a reduction in time to rehabilitation of 30%.

With significance levels of 8% (building size) and 20% (squared building size) respectively, some support for a nonlinear relationship between building size and time to rehabilitation is found. The relationship between building size and time to rehabilitation reaches a minimum at 1 million square feet, beyond which any further increase in building size has the effect of increasing the time to rehabilitation. Since this is near the largest building size in the sample, this means that most buildings are indeed on the negative sloping side of this curve. Therefore, an increase in building size reduces time to rehabilitation, except for very large buildings, where the impact is reversed.

Number of floors enters the regression with a positive sign, indicating that as the number of floors increases, time to rehabilitation increases as expected. The three 0-1 indicator variables for age of the structure in 1978 are negative and highly significant. As building age increases, time to rehabilitation decreases.

The five 0-1 indicator variables for location are a disappointment. The data do not support different rates of rehabilitation across different neighborhoods or market areas, which is somewhat unexpected. The coefficients of the 0-1 indicator variables for location are generally insignificant, except for Charleston where the coefficient is positive and weakly significant. Since there is a high correlation between the submarket indicators and the z variable, there may be multicollinearity problems here.

In column 3 of Exhibit 9, the estimators are slightly better in the sense of having smaller mean square error, than the estimators in column 2. There are two reasons for this. First, dropping the gain variable and using *AGE* as an instrument for z

eliminates a generated regressor on the RHS of the equation, which eliminates the issue of unobserved heterogeneity in the model. Second, using the *AGE* variable in column 3 eliminates the high correlation between gain from rehabilitation and building age, which permits a more accurate estimation of the building age effect. The results in column 3 also provide slightly better predictors from the model than those from the model estimated in column 2. Finally, comparing the results in columns 2 and 3, it can be seen that most of the coefficients in the latter equation are essentially unchanged. In particular, the coefficient of the rehabilitation tax credit changes only slightly, from −2.99 in column 2 to −2.97 in column 3. For these reasons (and since this research is mainly interested in prediction), the results in column 3 are preferred over those in column 2.

Regressions of time to rehabilitation were also performed on the control variables including the measure of the volatility in rent. Unfortunately, volatility in rent was highly correlated with the rehabilitation tax credit variable. Adding volatility in rent to the regression model resulted in a negative and highly significant coefficient, indicating, counter intuitively, that the higher the volatility in rent, the higher is the probability of rehabilitation. Also, by adding volatility in rent to the model, it is not surprising that the significance of the rehabilitation tax credit disappeared.

Other variables were also experimented with (e.g., vacancy rates), and while some of these variables were significant predictors of rehabilitation activity, the estimates of the other coefficients were not materially altered. In particular, the coefficient of the tax credit variable was robust.

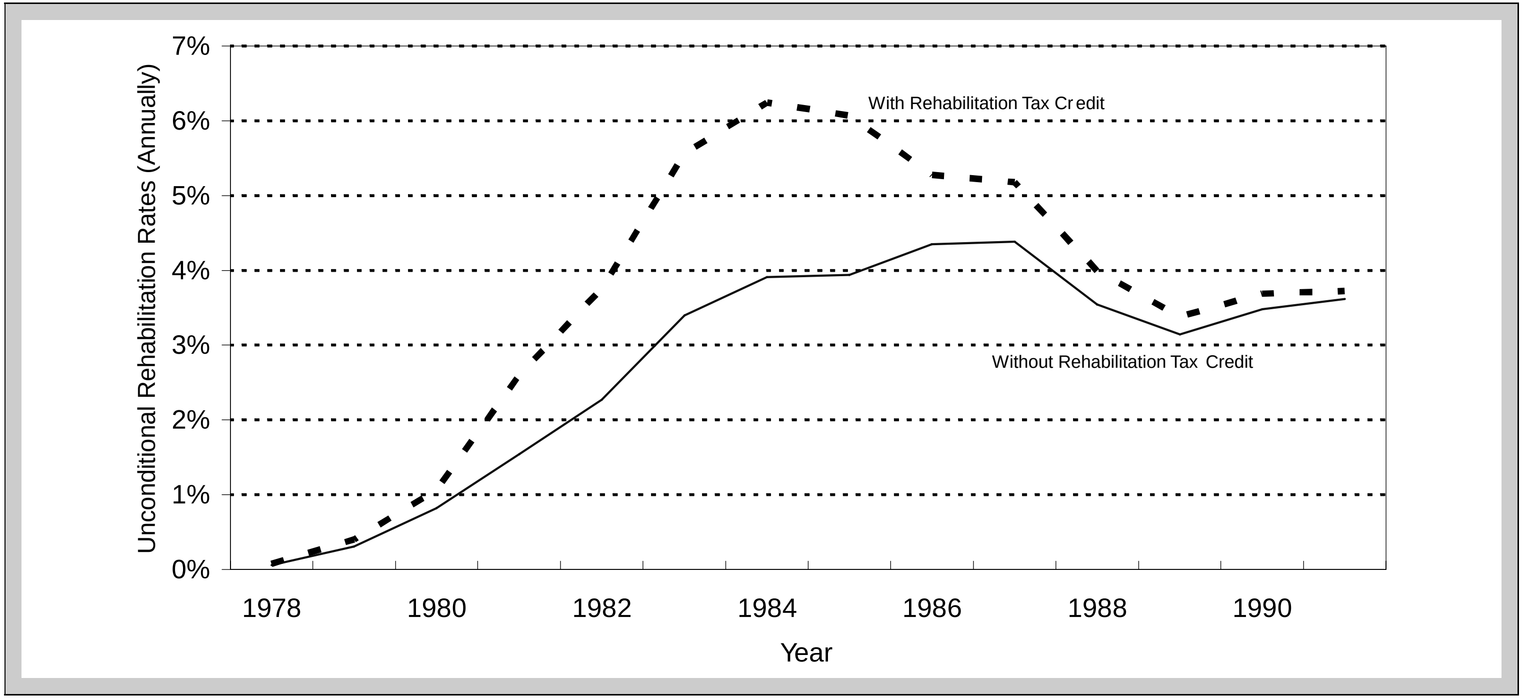
Policy Simulations

Even though the determinants of rehabilitation activity are not easy to unravel, the findings to this point have generally been expected in the sense that it is hard to believe that rehabilitation tax credits do not influence rehabilitation activity (and, perhaps, the amount of spending) in some manner. A more debatable set of issues arises as the focus shifts to the issue of slippage (i.e., the share of tax-credit investment spending that is spending that would have been invested otherwise).

To assess the degree of slippage associated with the rehabilitation tax credit, simulation analysis is applied to the proportional hazards regression model estimated above. While the focus is on column 3, in Exhibit 9, the full specification of the model without the gain from rehabilitation, the results are quite robust. The model is simulated twice: first assuming all exogenous variables take on their actual values (the ‘‘control simulation’’), and then assuming the value of the rehabilitation tax credit is replaced with zeros. Simulated probabilities of rehabilitation for each property are then averaged across all properties at each point in time. The results are then plotted in Exhibit 10. All calculations begin in 1978 and run forward to the end of 1991.

The simulations in Exhibit 10 offer several important insights. Notice first that, under the control simulation, the probability of rehabilitation is generally

Exhibit 10 | Simulation Results: Probability of Rehabilitation With and Without Rehabilitation Tax Credit

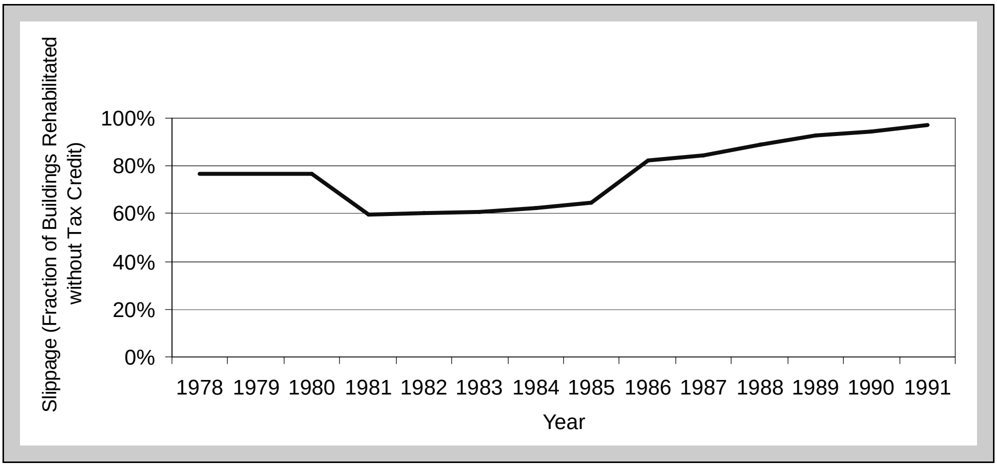


increasing in the 1979–1985 time period, and generally decreasing thereafter. The rise in the probability of rehabilitation during the 1978–1985 time period may reflect the increase in the rehabilitation tax credit during this period, while the fall in the probability of rehabilitation thereafter may reflect the fact that rehabilitation tax credits were reduced in 1986. However, this pattern may also reflect other factors such as increased, then decreased expectations of gain, or sample selectivity bias as the remaining population of buildings ripe for redevelopment dwindles.

Turning to the issue of slippage, the simulation results in Exhibit 11 suggest that during the 1978–1980 time period, roughly 75% of the rehabilitation tax credit was dissipated on investors who would have invested anyway (as measured by the ratio of the fraction of buildings that were predicted to be rehabilitated in the absence of the rehabilitation tax credit to the fraction of buildings that would have been rehabilitated under the control simulation).[18] On the other hand, in the 1981–1985 time period, the results suggest that only 60% to 65% of the rehabilitation tax credit was dissipated on investors who would have invested anyway. This figure increases to roughly 90% in the 1986–1991 period. Thus, moving chronologically through the time period analyzed here, the degree of dissipation generally starts out fairly high, then decreases, only to increase thereafter. These results are entirely consistent with theoretical expectations. They confirm the fact that significant slippage does occur. They also suggest that such slippage can be compounded (and tax credits rendered increasingly less effective) as the remaining population of buildings that are potential candidates for rehabilitation dwindles.

The ultimate question is whether the tax credit increases or merely accelerates the level of rehabilitation. The high degree of slippage in the late 1980s as the

Exhibit 11 | Simulation Results: Slippage



(Annual Fraction of Buildings that Would Have Been Rehabilitated in the Absence of the Rehabilitation Tax Credit to the Fraction of Buildings That Would Have Been Rehabilitated Under the Control Simulation) population of eligible buildings declines suggests the latter to be primarily the case, but a thorough evaluation of this issue depends on a competing risks framework that also considers the decision to demolish, as well as to rehabilitate. Such a framework is not a part of the current analysis.

Conclusion

In this work, evidence is presented in a new but obvious way that demonstrates that rehabilitation tax credits have important effects on the timing of rehabilitation decisions as expected. Evidence is also presented that suggests that a significant portion of rehabilitation tax credit investment spending is spending that would have been invested otherwise. This portion, however, is lower in high tax credit regimes *ceteris paribus*. These latter findings have not been fully considered or looked at by the previous literature on investment tax credits.

The evidence is generally supportive of the view that a higher expected gain from rehabilitation leads to higher rates of rehabilitation. However, the specification of gain from rehabilitation is measured with errors. It is also, by definition, highly correlated with building age. In response to these problems, two models of the time to rehabilitation are estimated: one that includes gain from rehabilitation and building age (plus other RHS variables), and one without gain from rehabilitation (but including building age plus other RHS variables). A model conditional only on the gain from rehabilitation is also estimated to study the sensitivity of estimates of the coefficients to different specifications.

Although perhaps obvious, it is worth stressing that the relationship between time to rehabilitation and building age ought to be fairly strong. There are numerous reasons for expecting this. Empirically, the results presented above generally confirm the expectation that building age is a critical determinant of time to rehabilitation, with the sign as expected.

It also is interesting that neighborhood influences are generally insignificant. This result runs contrary to argument of Davis and Whinston (1966), and others; however, it too may be affected by collinearity with the gain and age variables.

In closing, there are some limitations to the results. First, the focus alone on the level of rents (as well as vacancy rates) is not meant to deny that other economic factors such as office employment growth can have significant effects on rehabilitation activity. For the present, the data simply do not encompass these other factors (other than implicitly through the market rents). In addition, an important assumption associated with the use of proportional hazards models is that all hazard rates should be time-separable. Obviously, to the extent that externalities or interdependencies between property values and neighborhood characteristics exist, and are reflected in the return on rehabilitation, this assumption may be violated. Finally, it can be argued that the treatment of censored observations is clearly critical to the results (particularly given the correlation between building age and right censorship).

Endnotes

[1] This is a restriction from prior law. Prior to TRA 1986, the credit extended to structures at least 30 years old.

[2] For a survey of this literature, see Gravelle (1993).

[3] Consider the work of Hendershott and Hu (1981), for example, who conclude that the cost of capital (and, hence, any investment tax credit) has a significant and substantial influence on investment in producers' equipment. However, this conclusion seems overstated because in their final set of estimated equations, the cost-of-capital variables generally lose their statistical significance. A part of the problem may stem from aggregation bias or measurement error. Another issue concerns the high degree of collinearity between the cost of capital and capacity utilization, which in fact is evident as soon as capacity utilization is entered as a regressor.

[4] Note that this does not imply that the only beneficiaries of the tax credit are those owners of older structures who would have rehabilitated their structures anyway. All owners of structures can eventually benefit from the credit as their properties age, their marginal revenue curves shift upward, and rehabilitation becomes efficient. The increase in consumer surplus for owners of property of age a_i due to the credit is the increase in the area between the marginal revenue curve MR_i in Exhibit 1 and the marginal cost curve from no credit (MC_0) to the appropriate credit level MC_j. Of course, none of this analysis considers what is often cited as the primary social benefit of the credit, namely the positive externality effects of eliminating blighted structures.

[5] In fact, in continuous time, structures would be expected to be rehabilitated at exactly that time in which the marginal revenue curve shifts upward and outward just sufficiently to cross the relevant marginal cost curve. At that point, the equilibrium level of rehabilitation q^* is defined by the point of crossover, where the excess profits generated from the rehabilitation are exactly equal to zero. In the real world, however, one must be concerned with the fact that the rehabilitation tax credit is permitted only for qualified structures that have been substantially rehabilitated. This requirement means that investors might postpone rehabilitation into the future until the time when the cost of renovating qualifies for the rehabilitation tax credit.

[6] Note that if $p = 1$, then there is no aging in $\lambda(t)$, which means that rehabilitation is a random event (and the expected time to rehabilitation for a building having survived to t remains the same, independent of t). However, if $p \neq 1$, then $\lambda(t)$ will either increase or decrease with time, which means that the rate of rehabilitation per unit of time should either increase or decrease depending on whether $p > 1$ or $p < 1$.

[7] To confirm expectations of the superiority of the Weibull specification, the hazard function was also estimated assuming a log-normal and exponential baseline hazard function. Although the log-normal model performed comparably to the Weibull, the exponential model was clearly inferior from the standpoint of maximizing the log-likelihood function.

[8] Both market and individual property vacancy rates are actually relevant in that they indicate both the tightness of the market overall and the tightness of the individual property relative to the market. However, the high degree of collinearity mandated use of only one, the property rate, which seemed to provide the most meaningful results.

[9] In the case of the few (2) buildings renovated before 1978, "effective age" was used, defined as the time since rehabilitation. The expected effect of age on time to rehabilitation is discussed below.

[10] Metropolitan level annual office rental data were taken from the *National Real Estate Index*.

[11] Rehabilitation is not explicitly defined in the survey, but is assumed to involve a substantial capital investment, which is intended to bring the structure up to its optimal level of economic productivity (i.e., where marginal revenue = marginal cost).

[12] No structures were demolished during the observation period.

[13] For details see Keifer (1988).

[14] However, it is also significant that the depreciable basis of a property is reduced by the amount of the rehabilitation tax credit. Also, the rehabilitation tax credit is permitted only for qualified structures that have been substantially rehabilitated, and which retain at least 75% of the existing external walls. The credit itself is limited to those expenditures directly associated with the rehabilitation; costs of acquisition or enlargement of such properties are not recognized expenses. See present IRS Code 47.

[15] Gain ‘‘before the tax credit’’ is used because the percentage rental increase is estimated before any consideration for the additional gain represented by the tax credit.

[16] As discussed earlier, the standard errors have been adjusted according to the procedure outlined in Murphy and Topel (1985) to take into account the incremental random sampling error caused by the estimation, rather than the direct observation, of the gain z.

[17] The multicollinearity between the gain variable and *AGE* of course is not unexpected, given that the gain variable incorporated rent estimates that themselves were based upon *AGE* in the hazard equation.

[18] It is worth noting that simulations were also undertaken for the full hazard model in column 2. Results were comparable to those undertaken for the model in column 3 with *AGE* but without the gain variable.

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